Fractal Time Series Analysis of Human Heartbeat Intervals for Physical and Mental Workload

Sheldon M. Russell

Gregory J. Funke

Benjamin A. Knott

Matt Middendorf

FRACTAL TIME SERIES ANALYSIS OF HUMAN HEARTBEAT INTERVALS FOR PHYSICAL AND MENTAL WORKLOAD

Sheldon M. Russell, Gregory J. Funke, Benjamin A. Knott, Matt Middendorf

Air Force Research Laboratory
Wright-Patterson AFB, OH

As the environments and tasks that teams (in both military and civilian settings) are faced with increase in complexity, standard statistical methods may not fully capture team dynamics and processes. Nonlinear analyses provide alternative, mathematically derived descriptions quantifying the level of complexity and variability inherent in a data set, and may provide a more accurate understanding of dynamic systems. The goal of the present study was to investigate changes in heart interbeat interval associated with task workload using one type of nonlinear analysis, power spectral density analysis. In this study, physical and mental workload were manipulated in separate tasks to explore the contributions of each to interbeat interval variability. Results indicated that spectral analysis can identify large changes in overall workload, but may be insensitive to small or medium changes. However, these conclusions are based on preliminary results; follow-up research is necessary to determine the veracity of these conclusions.

Introduction

Although a relatively new addition to the sciences, the study of nonlinear dynamical systems (formerly known as chaos theory) has yielded interesting findings in a variety of scientific disciplines (an easily accessible general overview of this body of work can be found in Gleick, 1998). These types of systems (referred to from here on as *fractal systems*) are characterized by complex interdependencies in system variables and often unpredictable long-term outcomes. Long term weather patterns are a primary example of this, as the many interdependent factors associated with weather (humidity, solar activity, cloud cover, etc.) make long term predictions of specific weather outcomes very difficult. Although long-term outcomes are unpredictable, studying the behavior of systems over time (via time series analysis) has led interested researchers to conclude that, though specific predictions are not possible, fractal systems will generally behave in structured ways across time and scale, a property known as self-similarity. A variety of mathematical techniques are available to assess the fractal characteristics (including self-similarity) of a system, but the type of interest here involves frequency analysis of the time series output from a system.

Fractal analysis of time series data can involve a variety of frequency analysis techniques, such as Fourier transform, Lomb-periodogram, and wavelet analysis (Malamud & Turcotte, 1999). The goal of frequency analysis is to break the time series into frequency components (sine and cosine base signals) to determine the power spectral density characteristics of the time series. Correlations between these frequency characteristics indicate specific attributes of the system that produced the time series. Specifically, systems that are fractal in nature produce a power spectral density plot that has a power-law distribution (as opposed to, for example, a normal distribution). When the probability of measuring a specific value varies inversely as a function of a power of that same value, it is said to follow a power law.

Many natural systems, including biological processes such as cardiac interbeat intervals (IBIs), have been shown to fit a scaling that has power-law characteristics (see Newman, 2005, for a review). In the area of nonlinear applications to heart rate variability and IBIs, most research has focused on medical applications, examining cardiac risk (Goldberger, 2002), gender differences (Ryan et al., 1994), as well as determining baseline or normal resting heart rate characteristics (Ivanov et al., 1999). For an overview of fractal geometry research in biological systems, including the human heart, see Iannaccone & Khokha (1996).

In addition to research focused on fractal characteristics, other measures of heart rate variability have previously been explored as indices of cognitive workload and stress (see, e.g., O'Donnell & Eggemeier, 1986, for a review). Such research typically compares mean IBI variability across conditions for evidence of differences attributable to experimental manipulations. Overall, decrements in heart rate variability have been observed with increases in mental workload (Kalsbeek, 1971; Kalsbeek & Ettema, 1963). These decrements appear in frequency ranges similar to those reported in the cardiac nonlinear analysis literature.

In the present research we utilized the Fourier transform method, as previous research has demonstrated its accuracy as a method for determining the fractal characteristics of typical heart rate data (McSharry & Malamud, 2005). The following equations were reported in McSharry & Malamud (2005), and describe the Fourier transform of IBI time series data (x_n), where the total duration of the time series, *T*, is divided into *N* intervals of size $\delta = T/N$:

$$X_k = \delta \sum_{n=1}^{N} x_n e^{2\pi ink/N}, \quad k = 1, \ldots, N, \qquad (1)$$

and

$$x_n = \frac{1}{N\delta} \sum_{k=1}^{N} X_k e^{-2\pi ink}, \quad n = 1, \ldots, N. \qquad (2)$$

The power-spectral density function S_k is then defined as:

$$S_k = \lim_{N \to \infty} \frac{2|X_k|^2}{N\delta}, \quad k = 1, \ldots, N/2. \qquad (3)$$

While in general fractal systems follow power law scaling, correlations between values of S_k for all reported frequencies further specify characteristics of the system that generated the time series. Correlation values for spectral densities typically are reported as $\beta = x$, where x is the value of the exponent in the power equation multiplied by -1. For example, white noise (and other random processes) result in $\beta = 0$, in that there are no correlations between power spectral densities at any frequency value in the time series. Processes with long range correlations (i.e., preceding time series values influence subsequently observed values, a phenomenon termed *persistence*), result in correlations of $\beta = 2$, often called Brownian motion. A very common finding in natural systems is a correlation of $\beta = 1$, often referred to as $1/f$ noise or pink noise. Systems characterized by pink noise are not random, in that frequency values are correlated; however, these systems are not as persistent as systems characterized by Brownian motion. Previous research indicates that, in healthy individuals, a normal, resting cardiac IBI exhibits pink noise characteristics for frequencies below .1 Hz (e.g., McSharry & Malamud, 2005).

In general, deviations from β values of 1 have been shown to be associated with abnormal heart function and health risk. In the most extreme cases, β values of 0 indicate that the heart is fibrillating, and β values higher than 2 indicate states of congestive heart failure. The emerging consensus is that normal, healthy hearts display regular variability in IBI, and too much or too little variability can create significant problems (Iannaccone & Khokha, 1996). The complex nature of heart rate variability has led some to conclude that heart rate dynamics can be termed *multi-fractal*, in that the heart has a variety of different variability characteristics depending on the demands placed on the cardiovascular system (Ivanov, 1999).

Since fractal analysis of IBI has been demonstrated to be diagnostic in clinical settings (e.g., Goldberger, 2002), it is possible that the fractal dynamics of a heartbeat time series may also provide a sensitive index of workload and stress, and yield new insights into human performance. Of particular interest is the possibility that fractal indicators of workload may be more sensitive than averaged measures when comparing across individuals due to the computational process required for analysis. This process essentially normalizes the data to the frequency domain, thereby reducing individual differences often associated with physiological measures, which should result in increased sensitivity (Malamud & Turcotte, 1999).

Within the domain of workload and team performance, an initial, exploratory study was conducted by Russell, Funke, Knott, and Knott (2009) to examine the fractal characteristics of IBI during a visual search task. Data for the analysis was drawn from an experiment conducted by Knott, Nelson, McCroskey, and Miller (2007). In that study, task workload was manipulated by varying the number of on screen distracters (8 or 48 objects) in a visual search task. The results of the analysis conducted by Russell et al. (2009) were relatively promising, indicating that it may be possible to observe differences in fractal exponents (β values) by manipulating task demands.

While the results from Russell et al. (2009) were encouraging, the experiment in that study was focused on visual search, rather than workload. The present study expands on the idea that changes in fractal exponents can be indicative of workload by testing several tasks. The present study also explores differences in physical and cognitive workload, with the goal of determining the sensitivity of fractal methods to sources and levels of workload. We initially hypothesized that the fractal exponents associated with primarily cognitive tasks would be differentiable from those associated with physical tasks. We also hypothesized that task difficulty would influence fractal exponents such that more difficult tasks would be associated with increased fractal exponent values. It is worth noting that the results reported herein are preliminary; data collection for this experiment is still ongoing.

Methods

Participants

24 people, 11 men and 13 women, between the ages of 18 and 30 participated in the experiment. Prior to participation, prospective participants were asked to confirm that they met the study's inclusion criteria, i.e., that they did not have abnormal heart conditions (e.g., heart murmurs, pace makers, etc.), that they were not taking any drug that would alter normal circulatory system function (e.g., blood pressure medications, blood thinning medications, etc.), and that they had abstained from caffeine and nicotine for 12 hours prior to the study. Participants who did not meet these requirements were not allowed to participate in the experiment.

Experimental Design

The current experiment utilized a 4 × 2 mixed design. The between-subjects factor was experimental task (mental arithmetic, anagrams, card sort, treadmill). For the purposes of description and subsequent statistical analysis, tasks were also grouped based on their primary sources of demand; mental arithmetic and anagrams required cognitive resources for task performance, and the card sort and treadmill tasks required physical resources. In the two physical task conditions, the within-subjects factor was trial (first, second). For the cognitive tasks, participants also completed 2 experimental trials, but these trials were further differentiated by a manipulation of task difficulty (easy, hard). All experimental trials were 20 minutes in duration. The primary dependent measure examined for this manuscript was the β values of the power spectral density analyses derived from participant heart inter-beat intervals (IBIs).

Cognitive Tasks

Two cognitive tasks (mental arithmetic and anagrams) were selected for this experiment as exemplars of task processes (i.e., working memory, mental computation, and verbal ability) utilized by many people during their normal work activities. In addition, these two types of tasks (i.e. mental calculation and verbal ability) have been used to evaluate the sensitivity and diagnosticity of more traditional measures of heart rate variability (e.g., Nickel & Nachreiner, 2003). The present study also featured a manipulation of task difficulty (easy, hard) between trials to examine the sensitivity of fractal analytic methods to variations in mental load. The order of the presentation (easy-hard or hard-easy) was counterbalanced across participants. A description of each task, including easy and hard conditions, follows below:

Mental arithmetic. In the easy condition, participants were required to calculate the sum of a pair of two digit numbers (e.g., 24 + 48) and input the answer using the keyboard. The hard condition required participants to divide a three digit number by a one digit number (e.g., 210 / 7). All answers in the hard condition were whole numbers. In both conditions, participants were free to respond to the problems at their own pace (i.e., there was no maximum response time to items).

Anagrams. Word lists utilized for this task were drawn from *The Teacher's Word Book of 30,000 Words* (Thorndike and Lorge, 1944). The easy condition included common four letter words; the hard condition word list was drawn from common 6, 7, and 8 letter words. Scrambled words were presented to participants on a computer screen, and participants were required to type in the correct word (e.g., "enes" was presented to the participant, and the correct response was "seen"). Each easy presentation was timed so that participants had 7 seconds to view the scrambled word and input the correct response; in the hard condition, participants had 10 seconds.

Physical Tasks

Two tasks (a card sorting task and walking on a treadmill) were selected to simulate physical exercise as might be encountered by many people during their day-to-day work activities. These conditions were included to examine the sensitivity of fractal analytic methods in discriminating physical and mental sources of task load. As in the cognitive tasks, participants completed two 20-minute trials. However, the experimental task in each trial for the physical tasks was identical. This arrangement was selected to assess the effects of light fatigue on β values and to ensure that the duration of all tasks were comparable. A short description of each physical task is included below:

Card sort. The card sorting task was chosen to generate physical workload levels akin to light office work. Two tables were set up 10 feet apart from each other. Each table contained 8 decks of shuffled playing cards. Participants' task in this condition was to sort a deck of cards (by number) at one table, then move to the second table and sort a second deck of cards. This process (moving between tables and sorting cards) was repeated for the duration of the trial.

Treadmill. The treadmill task was designed to generate moderate physical workload. In the treadmill task, resting heart rate was established using averaged values from the baseline period. The task in this condition was to walk on the treadmill for the duration of the trial. The target heart rate for participants during each trial was 30% above resting baseline, and this goal was achieved by manipulating the speed of the treadmill, leaving the elevation setting at a 0° incline.

Heart IBI Recording

Heart rate information was collected using CleveMed Bio Radio devices sampling at 256 Hz. Custom software was written to detect R-wave peaks from the raw signal. This system required three surface electrodes attached to the participant to detect the electrocardiogram (ECG) signal. Electrodes were attached to the sternum in two places (the manubrium at the top of the sternum and the xiphoid process at the bottom of the sternum), and to the left clavicle (as a ground). The skin below the electrodes was prepared by cleaning each site with alcohol, and then applying NuPrep ECG skin abrasion gel to the site, gently wiping the skin with gauze, and finally applying the electrode pads. Heart rate data was recorded to text files and then imported into Matlab and Microsoft Excel for subsequent analysis.

Procedure

Participants first completed an informed consent document. Next, participants were asked to confirm that they met the study's inclusion criteria. Those who did not meet these requirements were not allowed to participate in the experiment. Participants were then assigned at random to an experimental task condition. The basic procedure for all experimental conditions was to first apply the electrodes and attach the heart rate monitor. Participants were then asked to sit quietly while a 5-minute baseline was recorded. Next, participants performed their assigned task during the first 20-minute experimental trial. Participants were then given a 15 minute rest break. Following the break, participants again completed a five-minute baseline and their experiment task.

Results

Spectral Analysis

All data files were imported into Microsoft Excel and cleaned for erroneous data points due to artifacts associated with the wireless radio devices. The final 1024 IBI intervals were taken from each time series and a segmented Fast Fourier Transform (FFT) with a Triangle window was performed on the data using Matlab software. The FFT segmented the data such that there were four unique 256 point analyses, and three overlapping 256 point analyses, with the average power at each frequency used for the final slope calculation. The resulting power spectral density for each participant was then plotted and β values were generated by calculating the regression slope for each participant.

Manipulation Check

As a manipulation check, the cognitive and physical tasks were examined for differences due to fatigue between the first and second experimental trials using separate paired sample *t*-tests (one for experimental task). Results of the analyses indicated there were no statistically significant differences between trials ($p > .05$ for all tasks), suggesting that fatigue did not influence spectral slope values in this experiment.

Task Difficulty

To examine spectral slope values for differences associated with task difficulty in the two cognitive tasks, a 2 (task) × 2 (task difficulty) analysis of variance (ANOVA) was computed. The results of the analysis revealed no statistically significant sources of variance in the analysis (all $p > .05$). These results indicate that the spectral slope values observed were similar across the cognitive tasks and task difficulties employed in this experiment.

Task Comparison

Given that the previously discussed analyses did not reveal statistically significant differences between trials due to experimentally manipulated factors, mean spectral slopes were calculated for each participant across experimental trials. As an index of the sensitivity of spectral slope values to task type, mean slope values for all experimental tasks were compared in a one-way ANOVA. The purpose of the analysis was to determine if spectral slope could be used to distinguish between primarily cognitive and physical sources of workload. Results supporting the sensitivity of spectral slope values would include a statistically significant main effect of task type, followed by statistically significant post hoc tests demonstrating differences between the cognitive and physical tasks.

Analysis of the spectral slope data revealed a main effect of task type, $F\ (3, 20) = 3.88$, $p < .05$. A follow-up post hoc Tukey HSD test indicated a statistically significant difference in spectral slopes between the treadmill and anagram tasks, and between the treadmill and mental arithmetic tasks. In addition, a trend in the data suggested a difference between the treadmill and card sort tasks ($p < .10$). No other comparisons were statistically significant (all $p > .05$). Mean spectral slope values for each condition are presented in Table 1.

Table 1. Mean spectral slope values for each experimental task.

Task	*M*	*SE*
Cognitive Tasks		
Anagrams	1.95	.17
Mental Arithmetic	1.88	.18
Physical Tasks		
Card Sort	1.86	.22
Treadmill	.97	.35

Note. M = mean, *SE* = standard error

Discussion

The goal of the present study was to examine the utility of a fractal analytic method, spectral slope analysis, as an index of workload. The results provide some interesting insight into the use of fractal measures of heart rate variability for assessing cognitive workload. We initially hypothesized that the fractal exponents associated with primarily cognitive tasks would be differentiable from those associated with physical tasks. This hypothesis was partially supported, in that both cognitive tasks had greater spectral slopes than those observed in the treadmill task. However, spectral slopes did not differ between the cognitive tasks and the card sort task. In addition, we hypothesized that task difficulty would influence fractal exponents such that more difficult tasks would be associated with increased fractal exponent values. This hypothesis was not supported; no differences were observed between the easy and hard task difficulty conditions for either of the cognitive tasks. It is again worth noting that these results are preliminary; our final results may differ from those discussed here.

The results concerning task type were more nuanced than initially hypothesized. Spectral slopes in the treadmill task differed from all other tasks, but no such differences were observed between the other three tasks. This seems to suggest that the fractal metric employed may not be sensitive to sources of workload (cognitive versus physical), but that it is sensitive to large differences in workload regardless of source. Although the current data seem to indicate that fractal techniques do not discriminate between physical and cognitive workload, the current data do suggest that light workload (i.e. using a computer, light office work) should not be a major concern in future experiments examining cognitive workload using fractal methods, as there were no significant differences between the card sorting task and the cognitive tasks examined in this experiment. This information is important for future research, as cognitive workload experiments are likely to include low levels of physical activity.

As mentioned previously, the results of the task difficulty manipulation employed in the current experiment did not match initial hypotheses in that the cognitive task conditions did not appear to generate changes in β values. This is at odds with the results reported by Nickel & Nachreiner (2003), who found mean IBI differences between verbal and other cognitive tasks. The results observed in the current experiment may be due to the manipulations themselves (i.e., the manipulations of task difficulty employed were insufficient to drive changes in β), or to relatively low power in these analyses (as overall N was relatively small). Alternatively, it may be that, unlike other measures of heart rate variability, β values do not lend themselves to observable differences based on workload manipulations (i.e., while IBIs follow power law scaling, β values may be relatively stable across individuals and most situations). Further research will be necessary to determine which of these alternative explanations is most accurate.

The results of this study indicate a strong need for future research. As previously mentioned, increasing the sample size reported here should provide greater statistical power for our analyses. To better understand the stability of β values under levels of workload, future research should explore the relationship of fractal heart rate variability with a greater diversity of workload levels and also in conditions more akin to "real world" tasks. More specifically, workload levels should include higher levels of cognitive workload than were employed in the present study, as our current results suggest that fractal measures appear to be sensitive only to large differences in workload. Furthermore, future research should also examine if fractal measures of workload are sensitive to changes between resting and working heart rates. Although baseline data was collected in this experiment, the duration of the baseline (5 minutes) provided an insufficient number of IBIs for a spectral analysis of the baseline period. Finally, future research should better address the issue of fatigue and cognitive workload. Although intertrial differences were not observed in the present experiment, it is likely that fatigue will exert some influence on fractal measures, provided that the task is of sufficient duration.

Overall, the (preliminary) results of the current experiment suggest that fractal analysis may yield useful metrics for understanding workload. At present, however, it appears that these metrics are unlikely to be more sensitive than those reported by previous researchers in the area (e.g., Kalsbeek, 1971; Kalsbeek & Ettema, 1963).

References

Gleick, J. (1999). *Chaos: Making a new science.* New York, NY: Penguin.

Goldberger, A., Amaral, L., Hausdorff, J., Ivanov, P., Peng., C., & Stanley H.E. (2002), Fractal dynamics in physiology: Alterations with disease and aging. *Proceedings of the National Academy of Sciences, 99*, 2466-2472.

Iannaccone, P. M. & Khokha, M. (Eds.) (1996). *Fractal Geometry in Biological Systems.* Boca Raton FL: CRC Press.

Ivanov, P., Amaral, L., Goldberger, A., Havlin S., Rosenblum, M., Struzik, Z., & Stanley, H. E. (1999), Multifractality in human heartbeat dynamics. *Nature, 399,* 461-465.

Kalsbeek, J.W.H. (1971). Sinus arrhythmia and the dual task method in measuring mental load. In W.T. Singleton, J.G. Fox, & D. Whitfield (Eds.), *Measurement of man at work* (pp. 101-113). London: Taylor and Francis.

Kalsbeek, J.W.H., & Ettema, J.H. (1963). Scored irregularity of the heart pattern and the measurement of perceptual or mental load. *Ergonomics, 6*, 306-307.

Knott, C.C., Nelson, W.T., McCroskey, M.K., & Miller, B.T. (2007). Do you see what I see? Effects of communication on scanning strategies in change detection by individuals and teams of observers. *Proceedings of the Human Factors and Ergonomics Society, 51*, 1186-1190.

Malamud, B.D. & Turcotte D.L. (1999). Self-affine time series: I. Generation and analyses. *Advances in Geophysics, 40,* 1-90.

McSharry, P.E. & Malamud, B.D. (2005). Quantifying self-similarity in cardiac inter-beat interval time series. *Computers in Cardiology, 32,* 459-462.

Newman, M.E.J. (2005). Power laws: Pareto distributions and Zipf's law. *Comtemporary Physics, 46*, 323-351.

Nickel, P. & Nachreiner, F. (2003). Sensitivity and diagnosticity of the 0.1-Hz component of heart rate variability as an indicator of mental workload. *Human Factors, 45,* 575-590.

O'Donnell, R., & Eggemeier, F.T. (1986). Workload assessment methodology. In K.R. Boff, L. Kaufman, & J.P. Thomas (Eds.), *Handbook of perception and human performance: Vol. 2. Cognitive processes and performance*, (pp. 42-1 to 42-49). New York, NY: Wiley.

Russell, S.M., Funke, G.J., Knott, C.C., & Knott B.A. (2009). Fractal time series analysis of human heartbeat intervals in a change blindness task. Proceedings of the International Society of Aviation Psychology. Dayton, OH, April 2009.

Ryan, S., Goldberger, A., Pincus, S., Mietus, J., & Lipsitz, L. (1994). Gender and age related differences in heart rate dynamics: Are women more complex than men?, *Journal of the American College of Cardiology, 24,* 1700-1707.