Cardiac Inter-Beat Interval Complexity Is Influenced By Physical Activity

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Abstract

The complexity of physiological signals may be a more sensitive indicator of health than standard or average measurements. We examined cardiac inter-beat intervals of healthy subjects who are either physically active or sedentary to determine whether measures of complexity are more sensitive to subtle cardiac changes than standard measures.

Subjects were pre-screened by self-report, and qualifying subjects were placed in either the active group \((n=10)\) or sedentary group \((n=10)\). Cardiac inter-beat intervals were recorded and subsequently analyzed using standard time and frequency domain heart rate variability measurements as well as multiscale entropy and the detrended fluctuation analysis, both measures of complexity.

Of the measurements, the detrended fluctuation analysis was the only tool that significantly \((P=0.04)\) differentiated between the active and sedentary groups. This suggests that the complexity of physiologic signals is a more sensitive indicator of cardiac health than standard measures.

Keywords: heart rate variability, detrended fluctuation analysis, multiscale entropy, aerobic exercise, non-linear dynamics
Introduction

The emergence of the field of non-linear dynamics, or chaos theory, in the last few decades has re-shaped much of scientific thought. We now know even fairly simple systems can exhibit complex behavior. In fact, in many systems there is such sensitivity to initial conditions that even insignificant noise can completely change their long-term predictability. Such chaotic systems are very unpredictable, but they are still deterministic and therefore not random. Non-linear systems tend to produce data that is somewhere between the predictable simplicity of linear systems and the unstructured nature of truly random systems. This middle ground, where data is unpredictable, yet has “meaningful structural richness,” (6) is sometimes termed complexity.

The prevailing method in studying physiological systems has been to average the output data. West (14) argues that averaging data can eliminate important, complex information embedded within the data. Using non-linear analysis tools in place of averages can help uncover information from complex physiologic signals that is otherwise lost. Studies using non-linear tools like the detrended fluctuation analysis (DFA) and the multiscale entropy (MSE) analysis show that data from healthy physiologic systems often contain a high degree of complexity while data produced by pathologic systems often have decreased complexity (5, 9, 11, 14). West (14) suggests that the complexity of physiologic systems may be affected by pathology before there is any noticeable difference in the average of the systemic output data. A high degree of complexity within physiologic signals, then, may be a better indicator of health than normal average values.

Complexity in cardiac inter-beat (RR) interval data, as measured by DFA and MSE, is associated with cardiac health, and a decrease in complexity is associated with cardiac pathologies (5, 8, 9, 14). Inasmuch as regular exercise has a positive impact on cardiovascular health this study was designed to address the concept of a relationship between RR interval complexity and physical activity. Rather than contrasting healthy versus unhealthy subjects, this study examines healthy young adults who are either
physically active or sedentary to determine whether a subtle, sedentarily-induced decrease in cardiac health can be demonstrated by altered complexity in RR interval data.

Tulppo *et al.* have shown that the DFA $\alpha_1$ value of sedentary subjects decreased after participating in eight weeks of aerobic training (12), indicating stronger fractal correlations and increased complexity in their heart rate dynamics. The present study focuses on the effects of long-term (> 1 year) aerobic exercise habits and includes MSE as a complementary means of measuring complexity. We hypothesize that the heart rate dynamics of healthy young adults who are physically active will have a higher degree of complexity than healthy young adults with a physically sedentary lifestyle.

**Methods**

*Subjects.* Male and Female subjects were recruited from the local university student population and gave written informed consent via a document approved by the University Human Subjects Institutional Review Board. Subjects self-reported physical activity level by filling out a questionnaire (Appendix A). The questionnaire was created by the authors for use in the present study and had not yet been tested for validity in its ability to precisely identify a person’s level of physical activity. Nevertheless, because the study called for two widely separated groups – either highly active or highly sedentary – rather than a spectrum of physical activity levels, the questionnaire’s ability to precisely quantify physical activity level was considered relatively unimportant for the present study. Subjects were invited to participate in the study if they had no serious health conditions, were between the ages of 18 and 40, and were either active or sedentary as defined by the questionnaire.

The physically active group ($n = 10$: 8 female, 2 male) included those who participated in aerobic exercise for a period of at least a half an hour with enough intensity to break a sweat at least 3-4 times each week, and had been doing so for more than one year. The age range of the physically active group was 20-26 years old with a mean of 22 (SD 2.1). The BMI range was 20.2-27.5 with a mean of 22.4 (SD 2.46).

The physically sedentary group ($n = 10$: 7 female, 3 male) included those who participated in aerobic exercise for a period of at least a half an hour with enough intensity to break a sweat one time or
less each month, and had been doing so for more than one year. The age range of the sedentary group was 21-39 years old with a mean of 25 (SD 5.6). The BMI range for the sedentary group was 18.7-28.2 with a mean of 23.8 (SD 3.63). There were no smokers in either group.

*Data Collection and Analysis.* Data collection took place between the hours of 800 and 2100 in a temperature-controlled room. Subjects were asked to refrain from alcohol and caffeine consumption for 6 hours prior to their data collection appointment. Upon arrival, subjects were instrumented with a Polar heart rate monitor chest belt transmitter, and then rested in a seated position for approximately 20 minutes. Immediately following the rest period, RR intervals were recorded for a mean of 8427 (SD 158) heartbeats (or approximately 2 hours) using the Polar S810i (Polar Electro Oy, Kempele, Finland) (3) while subjects rested quietly in the seated position. Subjects remained awake during the recording period and were allowed to read or do homework, but they refrained from any external stimuli such as movies or music.

Following data collection, the RR interval data was converted to text format using the Polar Precision Performance SW software (Polar Electro Oy, Kempele, Finland). Data was then manually inspected for artifacts (mean of 0.48%, SD 0.58%, range 0.0-2.16% in all subjects), which were subsequently deleted from the data set. For each subject, the publicly-available DFA and MSE software (4) were used to analyze the data, and Matlab (The Mathworks, Inc., Natick, Maryland) was used to plot the MSE output, plot the DFA output, and calculate the DFA $\alpha_1$ value.

Standard heart rate variability (HRV) measures, including SDANN, RMSSD, NN50, pNN50, VLF, LF, HF, LF/HF, and Poincare SD1, SD2, and SD1/SD2, were calculated using HRV Analysis Software version 1.1 (Professor Pasi A. Karjalainen, University of Kuopio, Finland). The standard lengths of RR data sets for these HRV measures are 5 minutes or 24 hours, depending on the measure (12). In the present study we recorded data for a non-standard interval of 2 hours, so our HRV analysis values should not be compared to values from other studies. We are primarily interested in determining the effectiveness of standard HRV measures to discriminate between the active and sedentary groups.
Measuring Complexity. DFA and MSE are non-linear tools that can measure complexity in time series data. In contrast to periodic/linear or random time series, complex time series often have correlations across time scales, i.e., small fluctuations at small time scales have similar characteristics to large fluctuations at large time scales. Both the DFA and MSE test for correlations across temporal scales.

The DFA (7, 8) is a quantitative measure of stochastic self-similarity, or fractal correlation, in time series data characterized by a scaling exponent, $\alpha$. While the physiological basis for the DFA $\alpha$ value is not well-understood, the $\alpha$ scaling exponent has proven useful in cardiology. Fractal correlations (an $\alpha$ value of 1.0) have been associated with healthy heart rate dynamics, and a loss of fractal correlations is associated with disease and aging (5). The short-term DFA scaling exponent, $\alpha_1$ (see reference 9 for further explanation), increases toward 1.5 as age increases (8). The $\alpha_1$ value is also considered the most reliable predictor of mortality in post-myocardial infarction patients—an $\alpha_1$ approaching 0.5 for those with high mortality risk (11).

MSE (10) is also a measure of complexity. It measures the entropy, or rate of information production, of time series data over varying scales. MSE has not been used in cardiology to the same degree as DFA, so its value in HRV analysis has not yet been established. Additionally, because MSE does not return a single value metric like the DFA or the standard HRV measures, it is more difficult to use for statistical comparisons. However, MSE plots associated with healthy cardiac dynamics have been shown to have constant entropy across scales, while the MSE plots of people with atrial fibrillation, congestive heart failure, or people who are elderly vary with scale (1, 2).

Results

The analysis results are summarized in Table 1.
Discussion

The DFA analysis indicates that healthy young adults who are physically active have a higher degree of cardiac complexity than healthy young adults who are physically sedentary. Our measured $\alpha_1$ value for the sedentary group was 1.20 compared to 1.02 for the physically active group—a value of 1.0 represents maximum complexity as measured by the DFA. For older, healthy adults, $\alpha_1$ values tend to approach 1.5 indicating that the sedentary group appears “older” in terms of cardiac complexity.

Our sedentary group did include one subject who was older than any subject in the active group, which theoretically could have confounded the DFA results, resulting in a false association between physical activity and the DFA $\alpha_1$ value. However, when the data of that subject was removed from the analysis, the statistical significance of the DFA as a differentiator not only held up, but improved ($P=0.03$). The DFA results were therefore not a result of age-related confounding, but of an actual difference in HRV complexity between the active and sedentary groups.

The MSE analysis, unlike the DFA, cannot be characterized by a single number; rather the complexity is indicated by the shape of the graph. Previous physiological applications of the MSE focused on differentiating between healthy and pathological conditions, which it did well in many cases. In our study, however, both groups were healthy – individuals in either group had no known pathological conditions. In our case, the MSE shows approximately equal levels of complexity in both the active and sedentary groups. Both the DFA and MSE successfully identified levels of complexity in the active and sedentary groups that are consistent with good cardiac health, but the MSE does not capture the differences between the two groups.

It is important to note, greater levels of physical activity were more strongly associated with a lower DFA $\alpha_1$ scaling exponent ($P = 0.04$) than with any of the standard measures of HRV ($P > 0.05$ for all standard measures). These results suggest that subtle differences in cardiac health are better detected by a change in the complexity of heart rate dynamics, as measured by the DFA in this study, than by more traditional methods.
The better sensitivity of the DFA versus traditional measures carries with it some practical implications. While it has been shown that traditional HRV measures used on ECG-derived data can successfully differentiate between physically active and sedentary men in a highly controlled environment (7), it is not practical for most fitness and training facilities to so tightly control the environment when their clients are analyzed. The present study suggests that the DFA can successfully differentiate between active and sedentary people, even when the environment is noisy— a much more realistic scenario in the real world. Moreover, the data for this study was taken for a relatively short period of time using a simple, widely available heart rate monitor rather than an ECG recording. Therefore, the DFA may be a more practical tool in fitness analysis.

The DFA may also have practical clinical applications. If, as the results of the present study suggest, the early stages of cardiac pathogenesis are better detected by altered HRV complexity rather than by traditional HRV measures, clinicians could use the DFA as an early indicator of risk for cardiac pathology. An earlier detection of at-risk cardiac patients via the DFA may help facilitate earlier intervention and, therefore, possibly better outcomes.

The results of this study may also have some philosophical implications. A movement is emerging in physiology away from using averages to smooth out physiologic fluctuations, and toward using non-linear tools to study complex information contained within the fluctuations (5, 13, 14). The term “homeostasis” suggests a simple, static physiologic state associated with health. A more fitting term may be “homeodynamics” (13) to reflect the complexity in fluctuations associated with healthy systems and the loss of complexity in pathologic systems—regardless of the average values for either system. The results of the present study support the paradigm of homeodynamics. Our results provide evidence that low levels of physical activity affects the complex dynamics of HRV before it affects the broad, traditional values such as average heart rate or BMI.

The scientific community has become expert at breaking systems down into their easily observable pieces and learning details about each piece. Problems sometimes arise, however, in trying to accurately rebuild complex systems out of the reduced pieces. Rather than trying to over-simplify
inherently complex physiologic systems, more studies should analyze the behavior of entire systems using ideas and methods from the field of non-linear dynamics. Because it appears that pathology presents itself as a change in the complexity of a system before it presents in systemic averages, tools that analyze the complexity of physiologic signals should be able to detect the onset of pathology earlier than systemic averages can. Therefore, emphasis in future studies should be placed on characterizing the differences in complexity of various pathologies compared to healthy complexity, as well as developing more tools for the analysis of complex physiologic information.

Practical Implications

• A new heart rate analysis tool can use simple data from a widely available heart rate monitor to effectively differentiate between active and sedentary people, even in a noisy environment.

• The heart rate analysis tool is more sensitive to subtle differences in heart health than standard measures, so it could be used clinically for earlier risk assessment, leading to earlier intervention and possibly better outcomes.
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References


Table 1 – Results Summary

<table>
<thead>
<tr>
<th>Measure</th>
<th>Sedentary – mean (SD)</th>
<th>Active – mean (SD)</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>DFA</td>
<td>1.20 (0.16)</td>
<td>1.02 (0.20)</td>
<td>0.04</td>
</tr>
<tr>
<td>SDANN</td>
<td>0.060 (0.015)</td>
<td>0.077 (0.032)</td>
<td>0.14</td>
</tr>
<tr>
<td>RMSSD</td>
<td>43.5 (18.2)</td>
<td>70.0 (42.0)</td>
<td>0.08</td>
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<tr>
<td>NN50</td>
<td>873 (623)</td>
<td>1390 (945)</td>
<td>0.17</td>
</tr>
<tr>
<td>pNN50</td>
<td>21.0 (15.2)</td>
<td>33.4 (22.7)</td>
<td>0.17</td>
</tr>
<tr>
<td>VLF</td>
<td>568 (274)</td>
<td>847 (600)</td>
<td>0.20</td>
</tr>
<tr>
<td>LF</td>
<td>829 (348)</td>
<td>1189 (867)</td>
<td>0.24</td>
</tr>
<tr>
<td>HF</td>
<td>418 (376)</td>
<td>1181 (1541)</td>
<td>0.15</td>
</tr>
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<td>LF/HF</td>
<td>3.187 (2.270)</td>
<td>1.707 (1.290)</td>
<td>0.09</td>
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<tr>
<td>Poincare SD1</td>
<td>31.2 (13.0)</td>
<td>50.2 (29.8)</td>
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<tr>
<td>Poincare SD2</td>
<td>97.2 (19.3)</td>
<td>121.3 (48.9)</td>
<td>0.17</td>
</tr>
<tr>
<td>Poincare SD1/SD2</td>
<td>0.31 (0.09)</td>
<td>0.40 (0.11)</td>
<td>0.07</td>
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<tr>
<td>Heart Rate</td>
<td>72.8 (6.76)</td>
<td>66.1 (10.2)</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Table 1: Comparison of several HRV measures in their ability to differentiate between RR interval data of active vs. sedentary subjects, as indicated by a statistical t-test P value. The only statistically significant measure (P<0.05) was the DFA.