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Dimensional Analysis of Actigraphic Derived Sleep Data

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Abstract: *Nonlinear dimensional analyses can be a useful tool in understanding the underlying behavior of dynamical systems, including biological systems. Many biological functions can be modeled as chaotic processes, including sleep. Sleep data can be obtained from several methods, such as electroencephalograms, polysomnography, and actigraph. Actigraphy, because of its low level of invasiveness, is an increasingly popular method of obtaining sleep data. This study analyzed actigraphy data with nonlinear dimensional analyses to determine if such analytic methods would be useful in sleep studies. Partipants wore actigraphs on their wrists, which recorded movement for several days. Several sleep quality variables, such as movement during sleep and total sleep time, were derived from these sleep data. These variables were used to determine whether the quality of sleep was good or poor. Lagged phase space plots were graphed and nonlinear parameters for the fractal dimension and the correlation dimension were computed for each participant. Descriptive and inferential statistics were performed to determine if the nonlinear parameters showed significant differences with respect to sleep quality.*

Key Words: actigraphy, sleep quality, correlation dimension, fractal dimension, nonlinear analysis

INTRODUCTION

Nonlinear dynamics have been used to describe many physiological systems, such as heart rhythms (Goldberger & West, 1987; Yeragani et al., 1998), speech pathology (Baken, 1990; Pean, Ouayoun, Fugain, Meyer, & Chouard, 2000), and sleep data obtained from electroencephalograms (EEG;

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Accardo, Affinito, Carrozze, & Bouquet, 2004; Acharya, Faust, Kannathal, Hua, & Laxminarayan, 2005; Kobayashi et al., 2000; Pereda, Gamundi, Rial, & Gonzalez, 1998). Analysis of sleep stages with EEGs using nonlinear analysis has shown considerable promise in differentiating sleep stages, such as awake, sleep stages 1-4, and sleep stage 5 (REM).

Actigraphs, also referred to as accelerometers, are instruments used to measure acceleration that have been used extensively to measure sleep. For sleep study purposes, they are typically watch-shaped devices worn on the wrist, 24 hours a day, recording movement at specified time intervals. The recorded data are processed using sleep algorithms to determine if a subject is awake or asleep, and also give the intensity of movement during wakefulness and sleep. Sleep quality ascertained by actigraphs has shown a high degree of correlation with results from polysomnography (PSG; Cole, Kripke, Gruen, Mullaney, & Gillin, 1992; Jean-Louis et al., 1996). One of the benefits of actigraphs is their non-invasive nature, in that they do not inhibit movement and can be worn at all times, unlike EEG and PSG, which require participants to be attached to equipment, allow less movement, and must be performed in a laboratory setting. Although actigraphy cannot differentiate between sleep stages or sleep disorders, as can EEG, actigraphy is used extensively by researchers who study sleep patterns and behaviors, from medical doctors and psychologists to laboratory scientists, due to its less invasive and data collection abilities.

Sleep quality is an important aspect of overall health. Poor sleep has been associated with illnesses, such as cancer (Carter, 2006) and depression (Gnirss, 1986), and with social factors, such as shift work (Vila, 2006). Poor sleep can have adverse effects on several mental and physical characteristics, including judgment, mood, and response time. Many population groups, including shift workers and emergency response workers, are at even higher risk of disrupted sleep patterns, which can become very erratic and nonlinear. The use of nonlinear techniques in determining differences in sleep quality adds another tool for researchers to use in sleep studies.

The aim of this paper is to show that the fractal dimension and correlation dimension of actigraphy data can be used to differentiate between study participants who have good sleep quality and poor sleep quality. Dimensional analysis can detect differences between sleep qualities due to increased physical activity during sleep and fewer sleep hours for those with poorer sleep. A study of health outcomes associated with stress among police officers includes research and analysis on how stress affects sleep quality. To help ascertain this, officers were asked to wear an actigraph in order to record their movement, which allowed us to determine the quantity and quality of their sleep.

METHODS

Participants

This investigation used data from the first 100 participants out of an anticipated 700 officers from the Buffalo Police Department, of which 58 were male (mean age: 44.0 ± 8.7 years) and forty-two were female (mean age: 44.0 ± 5.7 years). A general description of the study's design, methods and participant characteristics has been reported (Violanti et al., 2006). Data quality was checked, and twenty-one of 100 participants could not be used due to quality control issues, mostly from data corruption (Slaven, Andrew, Violanti, Burchfiel, & Vila, 2006). Three additional participants were excluded due to insufficient data; it has been shown that a minimum of five days of data are necessary for reliability (Acebo et al, 1999; Sadeh & Acebo, 2002).

Procedure

The Motionlogger actigraph (Ambulatory Monitoring, Inc, Ardsley, NY) was selected as the actigraph to be used. It recorded data as outlined above, with information recorded every minute, from which sleep quality statistics were derived. This actigraph also contained a time piece, allowing it to be used as a wristwatch as well. This area of placement also enabled the actigraph to detect acceleration along all three dimensions of movement. Participants wore Motionlogger actigraphs for 15 consecutive days, 24 hours per day, except for brief periods of time (e.g., while bathing or swimming). All phases, testing, and reports of the study were approved by the State University of New York at Buffalo Internal Review Board and the National Institute for Occupational Safety and Health Human Participants Review Board.

The output from the actigraph's primary integration mode (PIM) channel was used as the dependent variable to derive sleep onset and duration from activity data. PIM data analysis has been shown to be as effective as zero-threshold crossing and time-above-threshold in scoring sleep onset and duration (Gerardin, Kripke, Mason, Elliott, & Youngstedt, 2001).

Measurements

Sleep quality was assessed by measuring a number of variables, which were chosen from a literature search over studies involving sleep. Many studies have assessed the use of actigraphs in sleep studies, and a common set of variables have become standard (e.g. Lauderdale et al., 2006; Tikotzky & Sadeh, 2001). For this study, we chose the following variables: (a) wake-within-sleep, which gives the percentage of time a participant wakes up during sleep; (b) sleep-wake ratio, which is the ratio of the amount of time a participant is asleep to the amount of time they are awake; and (c) mean activity during sleep, which gives the amount of movement, measured in volts by the actigraph, which occurs during sleep. Correlation analysis was also performed, giving the additional variables: (d) maximum auto-correlation coefficients, which is a measure of how strong the regularity of their daily sleep patterns are; and (e) the time at the maximum correlation, which gives how far off this pattern is from a 24-hour cycle. Sleep quality was assessed by standardizing sleep variables, in order to give them all equal weight, and then taking the average of these standardized sleep variable values. To ensure that dimensional analysis was performed on participants who actually exhibited good and poor quality sleep, the remaining pool of 81 participants were divided into two groups, categorizing those who had the six highest overall ratings as having good quality sleep, and those who had the six lowest overall ratings as having poor quality sleep. These two classifications were used in order to examine the possible differences between possible study groups. In our case, the participants are healthy police officers who were not tested for any sleep disorder. Therefore, to find the possibility of differences between them, the extremes groups were compared. Descriptive statistics of these sleep variables for these twelve participants are given in Table 1.

Table 1. Mean and standard deviation for sleep quality variables.

	Good Sleep Quality		*Poor Sleep Quality*	
Sleep Variable	*M*	*SD*	*M*	*SD*
Maximum Correlation Coefficient	0.4	0.07	0.18	0.08
Lag Time From 24-hour Sleep Cycle	0.01	0.004 0	.07	0.11
Wake Within Sleep Percentage	10.42	1.66 2	4.77	2.32
Mean Activity During Sleep	196.87	29.76	372.83	37.45
Sleep Ratio	44.82	5.24 2	2.06	8.65
Fractal Dimension	1.68	0.11	1.85	0.06

Analysis Overview

Polynomial regression analysis was used to test for nonlinearity and the nonlinear analytic methods used in this study were lagged phase space plots, fractal dimension analysis, and correlation dimension analysis (Strogatz 1994; Williams, 1997). These methods were performed on the whole data file for each participant, using their time asleep as well as their time awake. The sleep cycle data gave information on how their actual sleep was affected by movement. The time awake gave information regarding actual amount of sleep.

Lagged phase space plots showed how the system changed and evolved over time, and was useful for visually determining patterns, orbits, and trajectories of the data. These graphs were obtained by plotting ordered values of the data, where the first component, $x(t)$, is the value of the variable at time t and the next component, $x(t+k)$, is the value of the variable at time $(t + k)$, where k is the lag, or delay, creating a plot on the Cartesian plane that gave a visual guide to the data. We varied the k values over a wide range in an effort to determine if there was a lag that would generate plots showing differences between good and poor sleep patterns, starting at a lag of one hour and going up to a lag of eight hours.

The fractal dimension, also called the similarity dimension, gives a measurement of how self-similar the data are. Self-similarity is a characteristic of objects that exhibit the same pattern at different scales of magnification

(West, 1990). To determine the fractal dimension of these data, the box-counting technique was used. The box-counting method of estimating fractal dimension is based on the concept of covering the graph of the data with a set of square boxes, or a grid, and counting the number of boxes that are filled by the data set. The log of the number of filled boxes is plotted against the log of the length of the box edges. This is repeated, reducing the length of the box edge each time, thus enlarging the number of boxes needed to cover the graph. A regression line is calculated for these points, in which the slope of the regression line is the fractal dimension (Smith, Lange, & Marks, 1996).

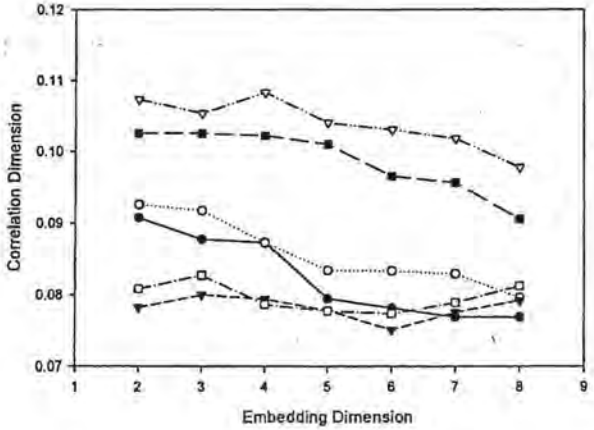
The correlation dimension is a measurement of the dimensionality of the underlying system. Unlike the fractal dimension, that only considers the geometry of the data, the correlation dimension tries to reflect not only the geometry of the system, but also the frequency that it passes through different areas of the phase space. This helps in accounting for the density of the points on the attractor. The correlation dimension is also typically smaller than the fractal (box-counting) dimension, due to its weighting scheme. The correlation dimension is found by taking each data point in turn and seeing if each of the other data points falls within a given radius. This is done multiple times, where a number of different size radii are used. This in turn is done multiple times, where the radii are dependent on the dimension of the circle. For example, each data point is compared to all others to see if they fall within a circle with radius = 1, then again for radius = 2, and so on. The points are then compared to each other to see if they fall within a three-dimensional sphere with radius =1, 2, 3, and up to the same radius used on the two-dimensional circle. It continues with a four-dimensional sphere and even further, up to a maximum dimension. The correlation dimension itself is defined as in Eq. 1,

$$C_r = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N} G(r-|x_i-x_j|), \tag{1}$$

where $|x_i - x_j|$ is the distance between two points, r is the given radius, and G is the Heaviside function. The Heaviside function is a function that gives values of zero or one, depending on whether the distance between the two points, x_i and x_j, is less than the radius. If the distance is smaller, the function assigns that pair a value of one, thus including it in the tally of pairs that fall within the given radius. As these values are summed up, they give the final total of pairs that are smaller than the radius r.

RESULTS

The test for nonlinearity resulted in the rejection of the hypothesis that the data were linear, with nonlinear terms being significant in the model ($p < 0.0001$). An embedding dimension of two was used for the lagged phase space plots. As the data were recorded every minute, a phase plot with lag = 1 minute would have too much information and would be too dense to discern anything. With our sets of lags ranging from one to eight hours, the eight hour lag gave the best visual graph while retaining enough information to maintain its usefulness. Regardless of sleep quality, most participants' phase plots had a very high percentage of the ordered pairs clustering in the corner. Most participants also had a very small number of outlying ordered pairs, giving a trajectory that branched out from the main cluster, but eventually went back in. However, none of the plots showed any large differences between the participants who had good sleep and those who had poor sleep. Different qualities of sleep most likely changed differently through time, but phase space plots could not graphically display this difference.



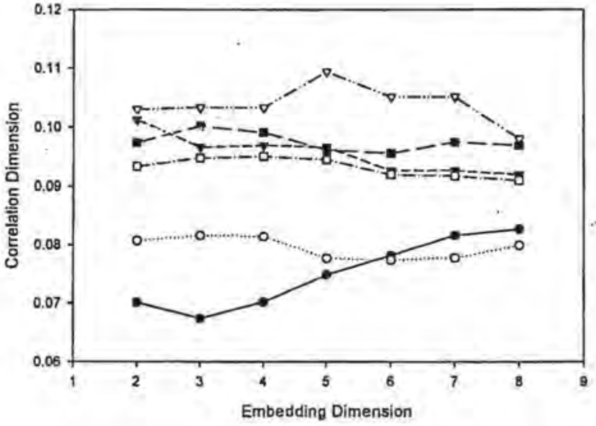


Fig. 1. Correlation dimension and embedding dimension for good quality sleep (left) and poor quality sleep (right).

Fractal dimensions (Table 1) showed a statistically significant difference between good quality sleep and poor quality sleep, from the Wilcoxon-Mann-Whitney U test ($U = 5.87$, $p < .02$). Good quality sleep tended to come from regulated sleep patterns and was characterized by few disturbances at night. Poor sleep quality data patterns showed a large amount of movement and wakefulness during normal sleep hours and less total sleep time. This caused the shape of the data to have activity spikes at night, taking up more space and adding complexity, which in turn caused their fractal dimensions to be higher than those acquired from good sleep data. Participants with poor sleep slept less each day, giving more overall activity.

The correlation dimension analysis (Fig. 1) showed that many dimensions are needed to model the differences between sleep quality data. A maximum embedding dimension of 8 was used, calculated from one of the general rules regarding embedding dimension and sample size, $2\log_{10}N$. Although there was no statistically significant difference in slope when examined by the Wilcoxon-Mann-Whitney U test ($U = 1.46$, NS), the graphs did show a difference between good quality sleep and poor quality sleep when analyzed with the correlation dimension. Good quality sleep was generally characterized by a slight, continuously decreasing slope, which showed that these data are simpler and require fewer dimensions for model building. Poor quality sleep data had slopes that had a slight increase or are nearly horizontal, giving evidence that these data were more complex, requiring more information and more dimensions to model, due to greater disruptions in the sleep cycle and a more irregular circadian rhythm.

DISCUSSION

Fractal dimensional analysis is useful in determining the quality of sleep when using actigraph data. Poor sleep quality is inherently more complex, due to a number of factors that may disrupt the circadian rhythm, such as movement during sleep, awakenings during sleep, sleep disorders, and shift work. Correlation dimensional analysis may not be as useful, however, due to the self-repairing nature of sleep. As the body will eventually force itself to sleep, unstable sleep patterns cannot persist for long periods of time. Correlation dimensional analysis may not be strong enough to detect differences between sleep qualities for this reason, while fractal dimensional analysis can detect differences over shorter time periods. Fractal analysis has also been shown to work very well in differentiating between different groups (Delignieres, Torre, & Lemoine, 2005).

A limitation to this study was that data collected in real world situations usually contain considerable noise and actigraph data is no exception. The Motionlogger actigraph recorded data every minute, giving us thousands of data points over the course of several days. This gave sufficient data for study, even though data with less noise would still have been better for these types of analyses.

A strength of this study was the large pool of participants from which to choose. This enabled us to purposely select participants who demonstrated good quality and poor quality sleep in order to determine if poor quality sleep could be differentiated from good quality sleep using dimensional analysis. Also, the use of actigraphy compared with the use of EEG or PSG methods of sleep analysis enabled us to get information on the total amount of sleep, given by the sleep-wake ratio, as well as information during sleep only.

Dimensional analysis can be used to detect differences in sleep quality. This analytic method gives researchers another tool in analyzing the quality of sleep, as well as potentially having the ability to determine how poor a participant's sleep can be. This method can also be used as a tool to determine the complexity of the data, allowing researchers the ability to better model sleep by determining the number of dimensions, and thus the number of parameters, needed to model different sleep patterns. Nonlinear analysis also allows researchers to focus on at risk populations whose sleep patterns deviate from typical sleep patterns, which could cause erroneous outcomes with standard linear analysis.

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