USAGE OF FRACTAL ANALYSIS IN EVALUATING HEALTH AND DISEASE

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INTRODUCTION

In recent years developments in the field of non-linear dynamics have led to new methods of evaluating physiological signals.[1] One promising method is the use of fractal analysis. Fractal analysis can be used to characterize patterns occurring in any data known to exhibit self-similar patterns.[2] These self-similar patterns are indicated by the repetition of trends in the data series, such as persistent patterns in which current data continues to follow the increasing or decreasing trends set by previous data in the same data set. A number of physiological biosignals have been found to exhibit fractal-like patterns, including: heart rate, blood pressure, EEG potentials, stride interval, and center of pressure displacement.[3]

Fractal analysis has proven a promising tool in differentiating healthy from diseased function.[2] Fractal analysis results in a quantitative measure, known as a fractal dimension, to describe the self-similar patterns observed in time-series data. Changes in the fractal dimension can represent changes in health. Such changes have been related to Parkinson's disease tremor, obstructive sleep apnea, epilepsy, fetal alcohol syndrome, and even sudden cardiac arrest.[4]

The aim of this study was to determine if fractal analysis could be applied to center of pressure measurements to differentiate the postural sway patterns of healthy young individuals, healthy elderly individuals, and individuals with Parkinson's disease. It was hypothesized that the postural sway patterns, as characterized by the fractal dimension, would be significantly different for those of advanced age and disease.

METHODS AND MATERIALS

Subjects

Ten individuals between the ages of 19 and 27; 22.6 ± 2.4 years, 171.5 ± 9.8 cm, and 66.9 ± 14.5 kg, comprised the healthy young (HY) group. Healthy individuals were those that self-reported being free of: any existing balance, neurological, or orthopedic disorders; a history of seizures, dizziness, or falls; or any surgeries or injuries to their legs that affected balance. Volunteers were excluded if they were diabetic, had suffered a stroke, or were taking any medications that had any side effects of drowsiness or dizziness. The healthy elderly (HE) group were those between the ages of 65 and 85 that met the same criteria of healthy. Ten volunteers; 73.2 ± 5.3 years, 162.9 ± 10.9 cm, and 69.3 ± 13.5 kg, met all inclusion criteria.

Ten additional individuals with Parkinson's disease comprised the group with known compromised balance (CB) due to disease. These individuals were assessed by their physician as having moderate disability due to Parkinson's disease (Hoehn and Yahr score II-IV), with some degree of postural instability. Individuals in this group ranged from 65-87 years old; 75.8 ± 6.6 years, 172.9 ± 8.2 cm, and 83.0 ± 24.0 kg.

The Institutional Review Board of The Ohio State University approved this study, and all volunteers gave written consent.

Data Collection

Center of pressure and related data were collected at 1000 Hz using a Bertec BP5050 balance platform (Bertec Corporation, Columbus, Ohio, USA). Subjects stood quietly on the balance platform, with arms to their side and looking straight ahead. Each trial lasted for 90 seconds, with two trials taken with eyes open (EO) and two trials taken with eyes closed (EC). Both anterior-posterior (A/P) and medial-lateral (M/L) data were collected during each trial. An FDA-approved safety support structure and harness were used for all testing.

Data Analysis

Moment data, used in the calculation of center of pressure, from the x-direction and y-direction of each trial were analyzed using Detrended Fluctuation Analysis to obtain a fractal dimension.[5] Detrended Fluctuation Analysis is a method of integrating and detrending the data series that allows for a scaling exponent to be calculated.[6] This scaling exponent can then be related back to the fractal dimension. The general idea of Detrended Fluctuation Analysis is to compare the root mean square fluctuations of best-fit curves fit to different ranges of data that are known to be fractal-like. Most commonly a linear relationship exists such that the smaller the amount of data being looked at, the smaller the fluctuations. When this linear relationship is plotted on a log-log plot, the slope is known as the α-scaling-exponent. The fractal dimension, FD, is then calculated as $FD = 2 - \alpha$.

Values of the fractal dimension range from 0.5 to 2. A fractal dimension close to 2 corresponds to a strong anti-persistent trend. In the case of balance, this means that the body tries to recover from movements made away from equilibrium by returning to a relative equilibrium position. A fractal dimension close to 1.5 indicates that all movement is random. A fractal dimension of 1 indicates a persistent long-memory trend, with positive correlations. In terms of balance this means that the person's center of pressure moves away from its relative equilibrium and continues to drift away, without recovering back. The relationships between data points for a fractal dimension between 1 and 2 are considered power-law scaling relationships and are often described as $1/f^{\alpha}$ scaling. A fractal dimension less than one suggests that though correlations may exist, they are no longer easily characterized by this power-law relationship and are therefore more difficult to describe.

Three different linear regions stood out on all detrended fluctuation plots of the moment data. Two of these corresponded closely to the regions Collins and DeLuca had previously acknowledged, having identified positive correlations at time intervals less than one second, and negative correlations at time intervals of one second or more.[7] Though Shimizu *et al.* acknowledge an existence of at least three distinct scaling-regions, the majority of research focuses only on the presence of either a single scaling-region, or the short- and long-term regions.[8] This study did not interpret findings corresponding to very short time intervals of 0-0.1 seconds. A short-term fractal dimension was determined for the linear region existing for time intervals 0.1 to approximately 1 second. A long-term fractal dimension was calculated for time intervals longer than 1 second. A custom-written Matlab script (The MathWorks, Natick, MA) was used to determine the crossover-point of one linear region to the other.

Statistical Analysis

Minitab statistical software (Minitab Inc., State College, PA) was used to perform one-way analysis of variance (ANOVA) tests on the means of the data. A series of null hypotheses were formed to determine if between-group differences for short-term, long-term and crossover findings. Null hypotheses were all formed to determine whether differences between sway directions and visual condition existed for the long-term region. All null hypotheses were rejected when $p < 0.05$. Tukey's Honestly Significant Difference test was performed ad-hoc.

RESULTS

Results for the short-term fractal dimensions are presented in Tables 1 and 2.

	A/P-EO	A/P-EC
HY	1.080 ± 0.25[a]	0.969 ± 0.16
HE	0.862 ± 0.18	0.804 ± 0.18
CB	0.817 ± 0.16	0.837 ± 0.18

Table 1. Summary of the short-term fractal dimensions for the A/P direction with eyes open and closed.

[a]Statistically significant from both HE and CB

	M/L-EO	M/L-EC
HY	1.006 ± 0.10[b]	0.958 ± 0.11
HE	0.894 ± 0.13	0.901 ± 0.14
CB	0.822 ± 0.22	0.833 ± 0.21

Table 2. Summary of the short-term fractal dimensions for the M/L direction with eyes open and closed.

[b]Statistically significant from CB group

Results for the long-term fractal dimensions are shown in Figure 1.

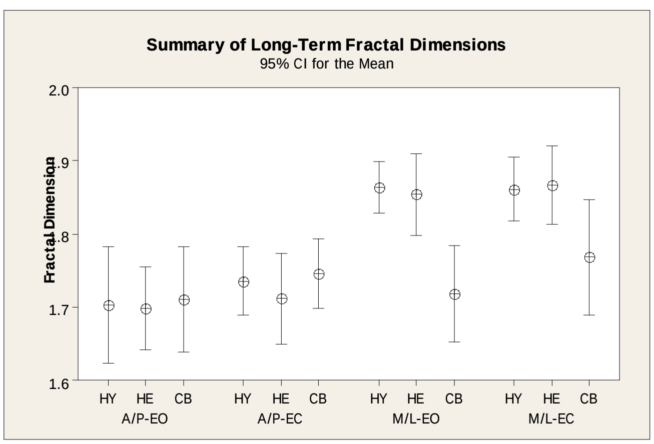

Figure 1. Summary of the long-term fractal dimensions for A/P and M/L directions with eyes open and closed. CB is statistically different than both HY and HE in M/L-EO and statistically different from HE in M/L-EC.

Statistical between group differences were found in several of the cases. Notably, the healthy younger individuals had a higher fractal dimension in the short-term region than both the healthy elderly and Parkinson's disease groups for the A/P sway direction with eyes open. In the A/P sway direction with eyes closed the healthy young group also had an average cross-over point higher than healthy elderly and Parkinson's disease groups, corresponding to a longer time spent in the short-term region by the younger individuals (1.83 seconds versus 1.00 and 0.99 seconds respectively).

The group with compromised balance due to Parkinson's disease was found to have a significantly lower long-term fractal dimension than the healthy groups in the M/L direction. With eyes open the Parkinson's disease group was distinguishable from both the healthy young and elderly, and with eyes closed the Parkinson's disease group was statistically different than the healthy elderly group.

DISCUSSION

The findings of this study revealed interesting information regarding postural sway that would not be picked up by most traditional analyses. The use of fractal analysis allowed patterns in the sway movements to be characterized and this enabled an easy, quantitative way to identify differences between the groups.

In all cases the short-term fractal dimensions were close to 1, corresponding to an extreme persistent pattern. A fractal dimension close to 1 indicated that during short time intervals subjects allowed themselves to lean increasingly further from their equilibrium position, without recovery. The crossover points indicated that this was the case for time intervals of a second or two. For time intervals longer than this all subjects switched to a more anti-persistent pattern, such that as they swayed away from equilibrium they would then compensate and recover back.

It was particularly interesting that older individuals, both with and without Parkinson's disease, stayed in the short-term region for a shorter amount of time than healthy young individuals. This may have to do with a decreased limit of stability, such that older adults cannot maintain stability while swaying to the extremes that younger individuals can. It may also have to do with lack of confidence and a fear of falling, such that older individuals are hesitant to fully explore their base of support. In either sense, it identifies an area of significant difference between young and older groups, and should be further examined to determine whether this difference may contribute to falls in the aging population.

Results showing that the sway patterns of individuals with Parkinson's disease could be distinguished from healthy individuals provide further support of the potential of fractal analysis in distinguishing health and disease. This study identified individuals with Parkinson's disease as having a more random sway pattern in the medial-lateral direction, consistent with a lower fractal dimension in the long-term region, than the healthy groups. This finding is in agreement with other literature that identifies individuals with Parkinson's disease as having a more complex side-to-side sway, and may explain some of the laterally directed falls sustained by this population.[9,10] This finding was particularly significant as it suggests the possible use of fractal analysis as a tool for disease diagnosis and to quantitatively monitor changes over time.

CONCLUSION

Fractal analysis has been shown successful in establishing healthy from diseased function in many physiological signals, such as EKG. This study applied fractal analysis to postural stability measures to determine whether advanced age or Parkinson's disease might affect sway patterns. It was found that differentiation was possible between the M/L sway patterns of Parkinson's patients and individuals who were healthy. These findings give insight into the sway patterns that would not commonly be observed by traditional clinical tools. Though further work is necessary, fractal analysis does show significant promise.

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