

Fractal Fluctuations in Breath Number, Period, and Amplitude are Independently Controlled in Awake, Healthy Humans

Gerard L. Gebber, Susan M. Barman, and Paul J. Fadel

Abstract- The present study was designed to characterize respiratory fluctuations in awake, healthy humans under resting conditions. Specifically, we used Allan factor and dispersional analysis to test whether the fluctuations in breath number, respiratory period, and breath amplitude were fractal or random in nature. The results can be summarized as follows. Fluctuations in all three parameters were fractal in nine subjects. There were four subjects in whom only the fluctuations in breath number and amplitude were fractal, three subjects in whom only fluctuations in breath number were fractal, and two subjects in whom only fluctuations in breath number and respiratory period were fractal. Fluctuations in the three parameters occurred randomly in the remaining two subjects. The data suggest that fractal fluctuations in breath number, respiratory period, and breath amplitude are controlled by separate processes.

I. INTRODUCTION

Unlike the anesthetized state, respiration in awake, healthy adult humans is characterized by considerable variability in the frequency, period, and amplitude (depth) of breaths [1]-[3]. The nature of the variability is dealt with in the current study. Specifically, we sought to answer the following questions. First, does the variability arise from random perturbations of the respiratory rhythm generator or deterministic processes? Second, if the latter is the case, do the time series contain long-range (time-scale invariant) correlations among events? Third, are the processes responsible for the variability in breath number, respiratory period and breath amplitude linked or independently controlled?

II. METHODS

A. Subjects

The recordings were made by P.J. Fadel at the University of Texas Southwestern Medical Center (Dallas, TX). The Institutional Review Board approved the protocols, and each of the 20 subjects (14 men and 6 women) provided written consent to participate in the study.

G.L. Gebber is with the Department of Pharmacology and Toxicology, Michigan State University, East Lansing, MI 48824

Phone: 517-353-8842; fax: 517-353-8915; email: gebber@msu.edu

S.M. Barman is with the Department of Pharmacology and Toxicology, Michigan State University, East Lansing, MI 48824

P.J. Fadel is with the Department of Medical Pharmacology and Physiology, University of Missouri, Columbia, MO 65212

This study was supported by National Heart, Lung, and Blood Institute Grants HL-33266 (to S.M. Barman) and HL-69648 (an Individual National Research Service Award to P.J. Fadel) and a Research Career Enhancement Award to P.J. Fadel supplied by the American Physiological Society.

The subjects were free of any known respiratory diseases and refrained from using tobacco, alcohol and caffeine-containing beverages for ≥ 12 h before the recording session. Their ages ranged from 22 to 58 yr and mean blood pressure and heart rate averaged 91 ± 2 mm Hg and 1.1 ± 0.1 beats/s.

B. Recordings

Recording sessions lasted 75-208 min, with the subject in a supine position in a quiet room and breathing spontaneously. Respiratory movements were recorded with a strain-gauge pneumograph placed in a stable position over the upper abdomen. Upward deflections in the raw records denote inspiratory movements.

C. Data Analysis

Data were acquired on an analog-to-digital converter (Axon Instruments, University City, CA). Using software developed at Michigan State University [4], [5], the peak and trough of each respiratory movement were detected and the following measurements made: 1) interval between peaks of successive breaths (referred to as respiratory period or peak-to-peak breath interval) and 2) trough-to-peak breath amplitude (normalized).

Allan factor analysis was used to determine whether fluctuations in the number of breaths in windows of specified length were random in occurrence or correlated over more than one time scale (i.e., fractal). Turcott and Teich [6] and Thurner et al. [7] define the Allan factor, $A(T)$, as the ratio of the event-number Allan variance to twice the mean number of events (i.e., respiratory cycles) in a window size of specified length (T)

$$A(T) = \frac{\langle [N_{i+1}(T) - N_i(T)]^2 \rangle}{2 \langle N_i(T) \rangle}$$

where $N_i(T)$ is the number of events in the i^{th} window of length T . The Allan variance is expressed in terms of the variability of the difference in the number of events in successive windows.

The Allan factor curve is constructed by plotting $A(T)$ as a function of the window size on a log-log scale. For a data block of length T_{max} , the window size, T , is progressively increased from a minimum of a single bin (40 ms) to a maximum of $T_{\text{max}}/6$. For a random process in which fluctuations in the number of events are uncorrelated, $A(T) = 1$ for all window sizes [6], [7]. However, for a fractal process containing long-range correlations, $A(T)$ increases as a power of the window size.

The power law relationship between $A(T)$ and window size appears as a straight line with a positive slope, α , on the log-log scale. The α (i.e., scaling exponent) is the power to which fluctuations in number of breaths measured on one

time scale are proportional (i.e., statistically self-similar) to those measured on other time scales. The correlation coefficient (r) is used to test for linearity on the log-log scale, and linear regression is used to calculate α .

Because the Allan α is bounded in a range of 0-3, it can be used to distinguish between two major classes of fractal processes, fractional Gaussian noise (fGn) and fractional Brownian motion (fBm). Cumulative summation of the elements of a fGn signal yields fBm, whereas the differences between the elements of fBm yield fGn [8]. Thus, fBm represents the integral of fGn. In theory, fractal time series with $0 < \alpha < 1$ are fGn, whereas the range $1 < \alpha < 3$ denotes fBm [8]. Taking the work of Thurner et al. [7] into account, we established a range of α (0.77-1.23) outside of which fGn and fBm could be distinguished. When the estimate of α was < 0.77 , the signal was classified as fGn. When α was > 1.23 , the signal was classified as fBm. When the estimate of α fell in the range of 0.77-1.23, the signal could not be classified.

Dispersional analysis (DA) was used to test whether fluctuations in respiratory period and breath amplitude were fractal. The algorithm as originally described by Bassingthwaite and Raymond [9] involves calculation of the standard deviation (SD) of the mean values of the measured parameter (peak-to-peak breath interval or trough-to-peak breath amplitude) for groups of data points of a specified number (m). The mean value for each group of m data points is obtained, and the SD of these values is calculated for the total number of groups. The process is repeated each time m is increased progressively from a minimum of one data point to a maximum of one-quarter of the total number of data points. In the present study, DA was performed on first differences derived from the original time series. This modification removes slow trends (i.e., nonstationaries) in the data [10]. Allan factor analysis, which is also based on first differences, similarly removes slow trends in the data [6], [7].

SD is plotted against m on a log-log scale, yielding a straight line with a negative slope. For a random process with no correlations among events, the slope of the DA plot is -0.5 [9]. For a fractal process, the slope is different from -0.5 over a range extending more than one decade of m .

The Allan factor curve and DA plots for the original time series are routinely compared with those of 10 surrogate data sets in which the intervals between breaths have been shuffled [3], [5]. Shuffling creates a randomized data set for which the mean, variance and frequency distribution are identical to those of the original time series, but with no correlations among events [6], [7]. If shuffling of the data eliminates the power law in the Allan factor curve and yields a slope of -0.5 in the DA plot, it can be concluded that the fluctuations of the measured parameters contained long-range fractal correlations.

III. RESULTS

Figure 1A illustrates the variability in respiratory period and breath amplitude observed in a spontaneously breathing 41-yr-old man. The raw record of respiratory movements (90 s in length) shows a segment of reasonably constant

peak-to-peak breath intervals and breath amplitudes followed by a relatively long respiratory period (12.6 s) and then considerable variability of the two measured parameters. The frequency distributions of 1,932 peak-to-peak breath intervals and 1,933 breath amplitudes recorded from this subject are shown in Fig. 1B and 1C, respectively. The mean peak-to-peak breath interval was 4.62 s (13.0 breaths/min) and the maximum peak-to-peak breath interval was close to 15 s. The frequency distributions were gamma like in shape.

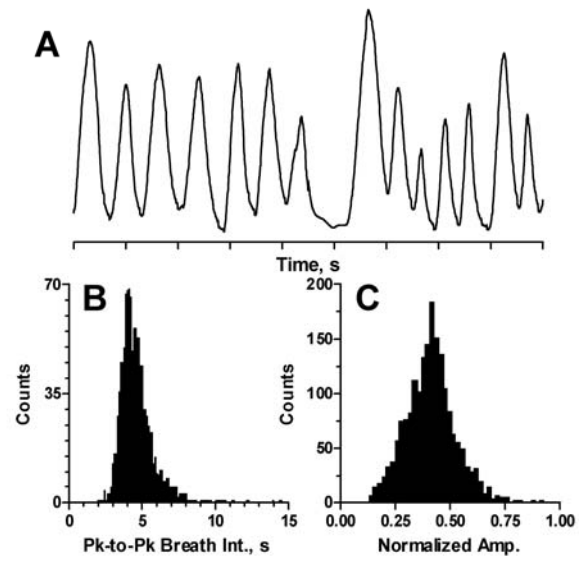


Figure 1. Breathing pattern in an awake human. A: respiratory movements recorded with a strain-gauge pneumograph. Inspiration is upward deflection. Time base is 10 s/division. B: frequency distribution of 1,932 peak-to-peak breath intervals with a coefficient of variation of 0.24. C: Frequency distribution of 1,933 breath amplitudes (normalized on scale of 0-1); coefficient of variation, 0.29.

The Allan factor curve and DA plots derived from a 143 min time series recorded in a 22-yr-old man are shown in Fig. 2. At window sizes < 2 s, $A(T)$ was close to 1.0 (uncorrelated data; Fig. 2A). $A(T)$ then dipped to < 1.0 before a power law appeared beginning at a window size of ~ 100 s (black trace in Fig. 2A). The dip in $A(T)$ is attributable to the strong periodic component of the respiratory signal [6], [7]. The power law extended over more than one time scale (i.e., decade) and its slope (α) was 1.35. Thus, this time series was classified as fBm. That the power law in the Allan factor curve indeed reflected long-range correlations among breath numbers is indicated by the fact that the curve derived from the original time series fell outside of the range of the curves for 10 surrogates (gray traces in Fig. 2A) at window sizes between 100 and 1,430 s.

DA demonstrated that fluctuations in respiratory period and breath amplitude were fractal in the same subject. The slope of the DA plot derived from the original time series of peak-to-peak breath intervals (dark trace in Fig. 2B) was -0.18 for $m \geq 5$, whereas the slope of the DA plot for the time

series of breath amplitudes was -0.10 for $m \geq 23$ (Fig. 2C). These slopes fell outside of the range of those (near -0.5) of the DA plots for 10 surrogates (gray traces). Thus, fluctuations in each of the three measured parameters were fractal in this case.

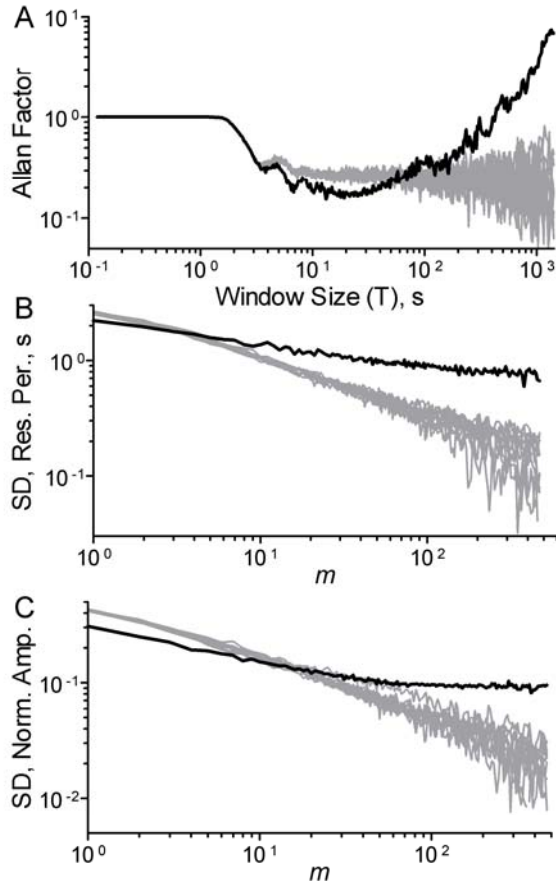


Figure 2. Fractal analysis of breathing pattern in a subject in whom fluctuations in number of breaths, respiratory period, and breath amplitude were fractal. A: Allan factor curves for original time series (black trace) and 10 surrogate (gray traces). B: dispersal analysis (DA) plot for original time series of peak-to-peak breath intervals (black trace) and 10 surrogates (gray traces). C: DA plot for original time series of breath amplitudes (black trace) and 10 surrogates.

Figure 3A-C presents a case (41-yr-old man) in which fluctuations in breath number and breath amplitude were fractal, but fluctuations in respiratory period were not. In this case, the slope of the power law in the Allan factor curve for the original time series was 0.41 (dark trace in Fig. 3A). Thus, this time series was classified as fGn. Note that the Allan factor curves for the surrogates were essentially flat after the initial dip in A(T). The slope of the DA plot for peak-to-peak breath intervals fell within the range of those of the plots for 10 surrogates at $m \geq 5$ (Fig. 3B). However, the slope (-0.29) of the DA plot for breath amplitude fell outside of the range of those of the surrogates at $m > 11$ (Fig. 3C).

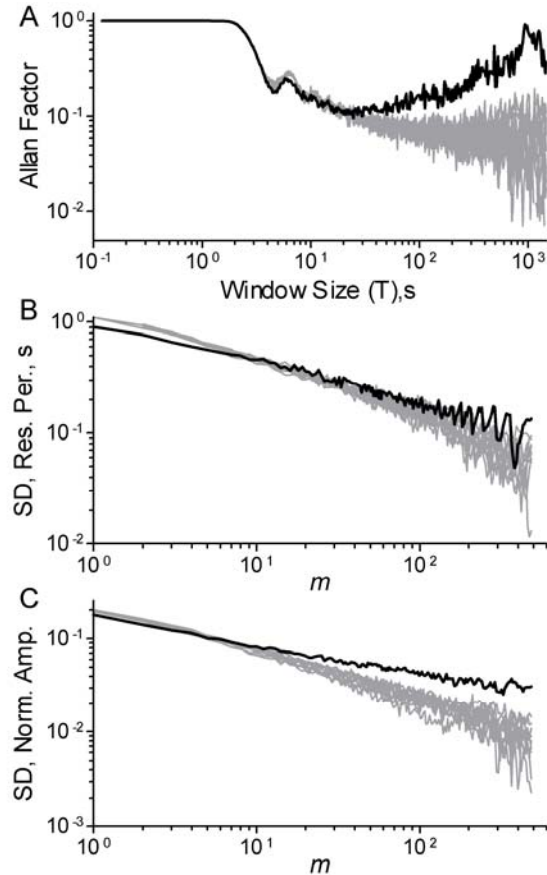


Figure 3. Fractal analysis of breathing pattern in a subject in whom fluctuations in breath number and amplitude but not respiratory period were fractal. A- C: sequence of traces is the same as in Fig. 2.

The results obtained in 20 spontaneously breathing subjects are summarized as follows. Fluctuations in all three measured parameters (breath number, period and amplitude) were fractal in 8 men and 1 woman. Fluctuations in breath number and amplitude, but not respiratory period, were fractal in 3 men and 1 woman. Only fluctuations in breath number were fractal in 3 women; and fluctuations in breath number and period, but not breath amplitude, were fractal in 1 man and 1 woman. Finally, the fluctuations in all three parameters occurred randomly in the 2 remaining subjects.

Using Allan α , we found that the fluctuations in breath number could be classified as fGn ($0 < \alpha < 0.77$) in 11 subjects and as fBm ($1.23 < \alpha < 3.0$) in 2 subjects. Allan α fell in the range of $0.77-1.23$ in 7 subjects. These cases could not be classified.

IV. DISCUSSION

Whereas respiration is generally treated as a rhythmic process, the variability in breath number, period and amplitude is, in fact, considerable in awake, healthy humans. The results of the current study clearly demonstrate that, in most cases, the variability in these parameters arises from

deterministic processes that generate fractal (i.e., time-scale invariant) behavior.

Fractal fluctuations in respiratory period [2], [11], [12] and breath amplitude [13] have been observed by others. Each of these studies, however, dealt with only one or the other of these parameters. Thus, to our knowledge, the current study is the first to determine whether the fluctuations in one or more of three simultaneously measured respiratory parameters were fractal in the same subject. Barring major differences in the sensitivities of the methods used to test for time-scale invariant behavior, our results point to the existence of separate fractal processes controlling breath number, period and amplitude. Perhaps the most intriguing cases (7 subjects) were those in which fluctuations in breath number were fractal when fluctuations in peak-to-peak breath interval were not. In these cases, the Allan factor curve contained a power law extending over more than one time scale, but the DA plot for peak-to-peak breath intervals had a slope in the range of those of the plots for the surrogates. These data support the existence of a “fractal rate code” in which fluctuations in breath number, but not respiratory period are ordered. On the hand, there were 11 subjects in which DA demonstrated fractal ordering of peak-to-peak breath intervals. Such is referred to as “fractal temporal coding.” It is also clear that respiratory frequency and breath amplitude are controlled by separate fractal processes since there were five subjects in which the fluctuations in breath number, but not breath amplitude were time-scale invariant.

The mechanisms responsible for the fractal fluctuations in breath number, respiratory period and breath amplitude remain to be determined. One or more of the following factors might be involved in producing fractal fluctuations. First, fractal fluctuations might reflect the inherent properties of the respiratory oscillator. Second, peripheral feedback from the lungs and/or thoracic mechanoreceptors might lead to fractal fluctuations in respiratory pattern. Third, suprapontine inputs to the respiratory network might be a source of fractal fluctuations. Fourth, a feedback loop involving fractal fluctuations in blood-gas concentrations might be involved. Fifth, inputs to the respiratory network from the external world might be ordered as a fractal rather than random sequence of events. Sixth, fractal fluctuations in respiratory pattern might arise from changes in the level of wakefulness in our reclining subjects.

V. SIGNIFICANCE

Is it worth the effort to make the distinction between a fractal and a stochastic (i.e., random) time series? The answer to this question is yes for the following reasons. In contrast to a random process generating events that are independent of each other, fractal behavior is a property of a complex system whose many components generate processes on different time scales. Importantly, the processes generated on different time scales become linked due to nonlinear interactions of the elements comprising the complex system. As a consequence, long-range correlations of events appear in the physiological time series. Such time-scale invariant correlations reflect a form of long-term

memory in that the current value of the measured parameter is related to events in the distant past. It follows that such memory is potentially important in predicting future events. This, of course, is not possible for a random time series composed of uncorrelated events.

Fractal processes may also confer important adaptive properties to the system under study. For example, Goldberger et al [10] have suggested that linkage of processes on one temporal scale to those on other scales may prevent excessive mode-locking that would restrict the functional responsiveness of the organism to unexpected challenges.

Finally, fractal fluctuations in breath number took the form of fGn in some subjects and fBm in others. The physiological significance attached to each of these two classes of fractal signals and their interconvertibility remain to be determined.

REFERENCES

- [1] M.J. Tobin, M.J. Mador, S.M. Guenther, R.F. Lodato, and M.A. Sackner, “Variability of resting respiratory drive and timing in healthy subjects,” *J. Appl. Physiol.*, vol. 65, pp. 309-317, 1988.
- [2] C.K. Peng, J.E. Mietus, Y. Liu, C. Lee, J.M. Hausdorff, H.E. Stanley, A.L. Goldberger, and L.A. Lipsitz, “Quantifying fractal dynamics of human respiration: age and gender effects,” *Ann. Biomed. Eng.*, vol. 30, pp. 683-692, 2002.
- [3] P.J. Fadel, S.M. Barman, S.W. Phillips, and G.L. Gebber, “Fractal fluctuations in human respiration,” *J. Appl. Physiol.* vol. 97, pp. 2056-2064, 2004.
- [4] G.L. Gebber, S. Zhong, C. Lewis, and S.M. Barman, “Differential patterns of spinal sympathetic outflow involving a 10-Hz rhythm,” *J. Neurophysiol.* vol. 82, pp. 841-854, 1999.
- [5] C.D. Lewis, G.L. Gebber, P.D. Larsen, and S.M. Barman, “Long-term correlations in the spike trains of medullary sympathetic neurons,” *J. Neurophysiol.*, vol. 85, pp. 1614-1622, 2001.
- [6] R.G. Turcott, and M.C. Teich, “Fractal character of the electrocardiogram; Distinguishing heart-failure and normal patients,” *Ann. Biomed. Eng.*, vol. 24, pp. 269-293, 1996.
- [7] S. Thurner, S.B. Lowen, M.C. Feurstein, C. Heneghn, H.G. Feichtinger, and M.C. Teich, “Analysis, synthesis, and estimation of fractal-rate stochastic point processes,” *Fractals*, vol. 5, pp. 565-597, 1997.
- [8] A. Eke, P. Herman, L. Kocsis, and Kozak, L.R., “Fractal characterization of complexity in temporal physiological signals,” *Physiol. Meas.*, vol. 23, pp. R1-R38, 2002.
- [9] J.B. Bassingthwaite, and G.M. Raymond, “Evaluation of the dispersal analysis method for fractal time series,” *Ann. Biomed. Eng.*, vol. 23, pp. 491-505, 1995.
- [10] A.L. Goldberger, C.K. Peng, J. Hausdorff, J. Mietus, S. Havlin, and H.E. Stanley, “Fractals and the heart,” in *Fractal Geometry in Biological Systems: An Analytical Approach*, P.M. Iannoccone, and M. Khokha, Eds. Boca Raton, FL: CRC Press, 1996, pp. 249-266.
- [11] U. Frey, M. Silverman, A.L. Barabási, and B. Suki, “Irregularities and power law distributions in the breathing pattern in preterm and term infants,” *J. Appl. Physiol.*, vol. 86, pp. 789-797, 1998.
- [12] P.D. Larsen, D.E. Elder, Y.C. Tzeng, A.J. Cambell, and D.C. Galletly, “Fractal characteristics of breath to breath timing in sleeping infants,” *Respir. Physiol. Neurobiol.*, vol. 139, pp. 263-270, 2004.
- [13] B. Hoop, H. Kazemi, and L.S. Liebovitch, “Rescaled range analysis of resting respiration,” *Chaos*, vol. 3, pp. 27-29, 1993.