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Nonlinear Analysis of Ambulatory Activity Patterns in Community-Dwelling Older Adults

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ABSTRACT

Background: The natural ambulatory activity patterns of older adults are not well understood. User-worn monitors illuminate patterns of ambulatory activity and generate data suitable for analysis using measures derived from nonlinear dynamics. **Methods:** Ambulatory activity data were collected continuously from 157 community-dwelling older adults for 2 weeks. Subjects were separated post-hoc into groups based on the mean number of steps per day: highly active (steps $\geq$ 10,000); moderately active (5,000 $\leq$ steps < 10,000 steps); and inactive (steps < 5,000 steps). Detrended Fluctuation Analysis (DFA), Entropy Rate (ER), and Approximate Entropy (ApEn) were used to examine the complexity of daily time series comprised of 1-minute step count values. Coefficient of Variation (CV) was used to examine time series variability. Between-group differences for each parameter were evaluated using ANOVA . **Results:** All groups displayed patterns of fluctuating step count values containing complex temporal structure. DFA, ER, and ApEn parameter values increased monotonically and significantly with increasing activity level ($p < 0.001$). The variability of step count fluctuations did not differ among groups. **Conclusions:** Highly active subjects had more complex patterns of ambulatory activity than less active subjects. The results supported the idea that, in addition to the volume of activity produced by an individual, patterns of ambulatory activity contain unique information that shows promise for offering insights into walking behavior associated with healthy aging.

Keywords: LONG RANGE CORRELATIONS, NONLINEAR ANALYSIS, PHYSICAL ACTIVITY, AGING, LOCOMOTION

INTRODUCTION

Common measures of walking performance (e.g., gait speed, distance walked) serve as important predictors of geriatric functional outcomes (1). They typically indicate that older individuals with frailty and / or disability often walk more slowly (2-4) and for shorter distances (5-7) than their healthy peers. Such walking performance measures, however, provide only a brief "snapshot" of walking ability under limited and highly controlled conditions; they do not capture the natural patterns of walking activity that emerge throughout the day as an individual engages from one moment to the next in meaningful tasks within their customary environment (8).

With a user-worn step activity monitor (9), ambulatory activity can be recorded for extended periods as a series of 1-minute step counts. Each series contains a 2-dimensional temporal structure: (a) a vertical structure comprised of raw1-minute step count values of varying magnitude, and (b) a binary horizontal structure comprised of minutes containing either some activity (step count > 0) or no activity (step count = 0) (Figure 1, Panel A). For a given individual, fluctuations in either raw 1-minute step count values (i.e., vertical structure) or the presence or absence of step activity (i.e., horizontal structure) form a unique pattern that reflects ongoing ambulatory interaction with the environment.

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INSERT FIGURE 1 ABOUT HERE

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Fluctuations in ambulatory activity are best quantified using measures of variation. Linear measures of variation (e.g., standard deviation) characterize the spread in a distribution of 1-minute step count values about their mean, without regard to the temporal

order in which values were collected. Nonlinear measures, in contrast, consider the extent to which the sequential ordering of 1-minute step count values is complex, and therefore, may contain meaningful information (10). The complexity of biological signals has been used previously to make inferences about underlying physiologic systems (11), such that aging and disease have been associated with diminished physiologic complexity and adaptability to stress (12-14). To date, the complexity of naturally occurring ambulatory activity patterns, represented as fluctuating step count time series, has received only cursory examination (8).

The purpose of this study was to explore the complexity of minute-to-minute fluctuations in step counts recorded daily from community-dwelling older adults over two weeks. Because complexity can be operationalized using a variety of theoretically different nonlinear methods, each of which offers a unique view of temporal structure, we employed a broad approach that included Detrended Fluctuation Analysis (DFA) (15), Entropy Rate (ER) (16), and Approximate Entropy (ApEn) (17) parameters. DFA was used to determine the extent to which the vertical structure of the daily step count time series remained approximately intact when viewed across multiple time scales. ER was used to examine the horizontal structure by quantifying the amount of uncertainty associated with whether step activity was recorded in any given minute. ApEn was used to augment the ER analysis by providing a theoretically similar approach that quantified uncertainty in the vertical, rather than horizontal structure of the daily step count time series. For comparison, minute-to-minute fluctuations in step counts from a given day also were characterized in linear terms using Coefficient of Variation (CV), a representation of standard deviation normalized to the mean 1-minute step count values.

METHODS

Subjects

Subjects were 157 community dwelling older adults recruited from the Veterans Affairs Medical Center and Duke University Medical Center in Durham, NC. Institutional Review Board approval was granted at both institutions. Potential participants were excluded if they were younger than 70 years old; were unable to walk inside their residence without human assistance; were living in assisted living or skilled nursing facilities; had active, unstable angina; uncontrolled hypertension; a medical or post-surgical order to purposefully restrict walking activity; were participating in other research that might influence walking activity; would not be living continuously in a solitary residence throughout their participation; because of cognitive impairment, required the assistance of a proxy to complete informed consent or study surveys.

Instrumentation

Subjects wore a SW3 step activity monitor (OrthoCare Innovations, Mount Lake Terrace, WA) for activity data recording. The monitor is the size of a pager, weighs 38g, is attached at the ankle using Velcro closures, and requires no maintenance by the user. It uses a combination of acceleration, position, and timing to detect strides taken by the leg of attachment. The monitor can be configured to record stride counts in 1-minute intervals, such that each 24-hour period produces a time series of 1,440 values. Data subsequently are downloaded to a personal computer using manufacturer software. During data processing, stride counts are doubled to reflect steps accumulated by both legs. Previously with older adults (18), the monitor has demonstrated good test-retest reliability (ICC, $r = 0.84$) and 96% accuracy; it has been particularly useful in accurately quantifying steps in populations

characterized by slow and/or shuffling gait (18-21).

Protocol

Subjects were instructed to wear the monitor 24 hours per day for 2 weeks, except when bathing, showering or swimming, and to refrain from aerobic exercise other than walking or jogging. The latter instruction was necessary because some types of non-ambulatory exercise (e.g., riding a bicycle) create vertical leg motion that produces spurious step count values. Subjects were contacted by phone only after the first monitoring day to address initial concerns.

Data Reduction

SW3 data processing typically requires only the manufacturer software to calculate simple summative measures from recorded step counts (e.g., daily number of steps or minutes of activity). In the present study, calculation of daily DFA (15), ER (16), ApEn (17) and CV values required the use of Matlab software (Mathworks, Natick, MA). In DFA, statistical self-similarity is quantified using a scaling exponent, α, to estimate inherent long-range correlations within each time series (15). Alpha values between 0.5 and 1 indicate positive persistence in temporal structure, such that data points are positively correlated with one another across multiple time scales. DFA is robust when applied to gait-based signals (22-24), especially when their underlying statistical properties tend to vary over time (15). Mean daily α values were computed for each subject.

Different types of ER have been used to analyze biological data (25-28). In the present study, we adopted a definition of ER based on Information Theory (16) and used it to characterize complexity in the horizontal structure of each daily time series (Appendix 1). Specifically, ER quantified the average amount of uncertainty associated with whether any

amount of step activity occurred at any given minute. Greater uncertainty implied that the ordering of active vs. inactive minutes contained a greater amount of information, and therefore, greater complexity.

ApEn (17) is a regularity statistic also based on Information Theory that was used to augment the ER analysis by quantifying the amount of randomness in the vertical structure of each daily time series. Specifically, ApEn determined the probability that short sequences of consecutive 1-minute step counts repeated, at least approximately, throughout the longer temporal sequence of 1,440 daily 1-minute intervals. ApEn generates a unitless real number between 0 and 2. Zero values correspond to a time series in which short sequences of data points are perfectly repeatable (e.g., a sine wave). Values of 2 correspond to time series for which repeating sequences of points occur by chance alone. Based on previous recommendations (29), we used a short sequence length (m) of 2 and an error tolerance (r) normalized to 0.2 times the standard deviation of individual time series for all subjects. We also applied a surrogation (phase randomization) procedure (30) to verify that the SW3 data were derived at least in part from a deterministic (non-random) source.

CV values were calculated for each daily time series of 1-minute step counts (CV = 100*(standard deviation / mean)). CV values represented the magnitude of variation of step counts relative to their mean, independent of the order in which step counts were accumulated.

Data Analysis

After data collection, subjects were separated into three groups based on the mean number of steps per day: highly active (steps $\geq$ 10,000); moderately active (5,000 $\leq$ steps < 10,000 steps); and inactive (steps < 5,000 steps) (31). Statistical procedures were performed

using SPSS 16.0 (SPSS Inc, Chicago, IL). Between-group differences in age, body mass index (BMI), DFA, ER, ApEn and CV values were determined using one-way ANOVA ($\alpha = 0.05$), with Tukey Honestly Significant Difference employed for post-hoc analyses. Pearson product moment correlations were calculated between various bivariate combinations of dependent variables.

RESULTS

Forty-six subjects were categorized as highly active, 86 as moderately active, and 25 as inactive. The average number of recorded minutes of activity per day was greatest among highly active subjects and least among inactive subjects (Table 1). All subjects completed two-weeks of data recording; no instances of missing days were identified. Mean age was statistically similar among groups [$F(2, 156) = 1.4$, $p = 0.2$]. Although BMI increased significantly with decreasing activity level [$F(2, 156) = 3.4$, $p = 0.03$], post hoc comparisons failed to reveal statistically significant between-group differences.

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DFA revealed the presence of long-range correlations within the vertical structure of step count time series ($0.5 < \alpha < 1.0$; Table 2). Between-group differences in mean daily α values were significant [$F(2,156) = 27.3$, $p < 0.001$]. Highly active subjects had significantly greater mean alpha values than both moderately active ($p < 0.001$) and inactive subjects ($p < 0.001$). Moderately active subjects had greater mean alpha values than inactive subjects ($p < 0.001$). The results indicated that fluctuations in 1-minute step counts generally contained complex, self-similar vertical structure, and that the vertical structure of highly active subjects was relatively more complex than that of inactive subjects.

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Between-group differences in ER values also were significant [$F(2,156) = 33.7$, $p <$

0.001] (Table 2.) Highly active subjects had greater mean ER values than both moderately active ($p < 0.001$) and inactive subjects ($p < 0.001$). Moderately active subjects had greater mean ER values than inactive subjects ($p < 0.001$). The results indicated that the horizontal structure of activity patterns recorded from highly active subjects contained more information, and therefore was more complex, than the horizontal structure of activity patterns recorded from less active subjects. Said differently, among highly active subjects there was relatively more uncertainty about whether or not activity occurred in any given minute.

ApEn revealed a similar pattern of significant between-group differences [$F(2,156) = 62.6$, $p < 0.001$] (Table 2). Highly active subjects displayed relatively greater amounts of randomness (i.e., higher ApEn values) in the vertical structure of the step count time series than either moderately active ($p < 0.001$) or inactive subjects ($p < 0.001$). Moderately active subjects had higher ApEn values than inactive subjects ($p < 0.001$). Greater randomness indicated greater uncertainty in the ordering of step count values. Given the deterministic source of the data, greater uncertainty was interpreted as greater complexity.

The CV results revealed that the magnitude of variation in 1-minute step count values was greatest for highly active subjects and least for inactive subjects (Table 2). Between-group differences, however, were not significant [$F(2,156) = 0.606$, $p = 0.55$]. For each group, the magnitude of variation in 1-minute step count values was slightly less than the mean 1-minute step count value.

Lastly, mean daily steps and minutes of activity were strongly related ($r = 0.81$, $p < 0.01$; Table 3). In general, nonlinear measures of complexity were positively correlated with mean daily steps, with 27 – 47% of their variance explained. Though generally positive, the

strength of associations among complexity measures varied; DFA was only weakly related to ER ($r = 0.14$, $p = 0.09$) and ApEn ($r = 0.22$, $p = 0.01$); ER and ApEn were strongly related ($r = 0.87$, $p < 0.01$). Each nonlinear measure of variation (i.e., DFA, ER, ApEn) was only weakly related the linear measure of variation (i.e., CV), with generally less than 12% of their respective variances explained.

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DISCUSSION

Many clinically useful analytical tools have been developed to provide relatively *instantaneous views* of aging walking function, from gait pattern analysis (32) to timed performance tests (4) to surveys of walking difficulty (1). What until recently has remained beyond the view of clinicians and researchers is a field-based methodological approach that offers an *ongoing view* of walking; that is, an opportunity to study the manner in which an older adult interacts naturally with his or her customary environment, beyond the spotlight of the clinic or laboratory. Indeed the characterization of walking as an interactive behavior is a central feature of contemporary human movement science (33). We speculate that patterns of ambulatory activity output, like other biological signals (e.g., blood pressure), have potential for determining the extent to which an individual adapts walking to changes in task demands and environmental conditions.

Measures of complexity examine the extent to which the ordering of data values in a long series of frequent measurements produces nonlinear patterns. In our study, DFA was used to determine the extent to which the vertical structure of the daily step count time series remained approximately intact when viewed across multiple time scales. The presence of long-range correlations in the ambulatory activity time series indicated a complex (i.e., self-similar) temporal structure to walking behavior. Regardless of activity level, minute-to-minute fluctuations in step count values were approximately similar to fluctuations unfolding over longer time intervals (e.g., hour-to-hour and day-to-day.) Importantly, highly active older adults displayed the greatest self-similar vertical structure in their patterns of ambulatory activity, whereas inactive older adults displayed the least. The determinants of the differences remain unclear. We suspect that highly active subjects routinely engaged in a

relatively wide array of indoor and outdoor ambulatory tasks and were more likely to venture from their homes to participate in community-level activities (34). For these individuals, patterns of ambulatory activity potentially could vary in dramatic fashion over multiple time scales (i.e., minute, hour, day). Inactive subjects, in contrast, presumably engaged in a narrower array of ambulatory tasks across fewer environments. Ambulatory activity in general, and especially outdoor, community-level activity, presumably would have been less frequent and more sporadic. We suspect, therefore, that the step count values of the inactive group were likely to have fluctuated relatively little from minute-to-minute and perhaps hour-to-hour; day-to-day fluctuations, however, may have been more dramatic, depending on whether or not a trip into the community occurred. Such differences across time scales would have produced relatively weaker long-range correlations for the inactive group.

ER evaluated the complexity of ambulatory activity data by quantifying the extent to which the ordering of active and inactive minutes contained "information," indexed as the uncertainty associated with whether activity or inactivity occurred in any given minute. The results again revealed that complexity was associated with activity level, such that there was relatively more uncertainty associated with whether or not highly active subjects were ambulatory in any given minute than for moderately active or inactive subjects. Unlike the DFA results, which we related to the types of tasks performed and environments utilized, we speculate that the ER analysis provided insight into the complex timing of ambulatory output that was apparent in the binary, horizontal structure of the data. Presumably the relatively wide variety of tasks and environments encountered by highly active subjects would inherently create a greater number of options for organizing various sequences of activity throughout the day. The ER analysis suggested that highly active subjects were more likely

to be “regularly irregular” in their activity patterns, whereas inactive subjects were more likely to structure their days in relatively more predictable ways. If confirmed, the result provides a rationale for studies of healthy aging that investigate the potential long-term benefits of variable behavioral routines and the disadvantages of highly structured, unchanging daily schedules.

ApEn provided a theoretically similar approach to the ER analysis. Like DFA, ApEn was applied to the vertical structure of the time series. Consistent with DFA and ER, ApEn revealed relatively more complex temporal structure in the ambulatory activity patterns of highly active subjects. Like ER, the result highlighted the unpredictability of minute-to-minute fluctuations in activity of highly active subjects and the relatively greater regularity in the activity patterns of less active subjects. Unlike the ER analysis, however, ApEn perhaps more strongly considered the specific demands of tasks performed and environments encountered by evaluating the vertical structure of the data. Thus, we inferred that the ApEn result supported the idea that a higher level of activity might be associated with an enhanced ability to adapt walking behavior to sudden changes in task demands or environmental conditions.

Moderate relationships between the mean daily steps and either DFA alpha values, ER values, or ApEn values highlighted the possibility that the complexity of ambulatory activity patterns may have simply served as a surrogate for activity level. Indeed we believe that as long as an activity time series contains raw step count values, it is reasonable to expect some correlations will exist between the mean daily steps and whatever other measures are being used. That being said, activity level did not appear the sole determinant of complexity. Compared to the predictably strong correlation across the sample between

mean daily steps and minutes of activity, relatively less of the variance in steps was explained by any nonlinear measure, especially DFA and ER. This result supported the idea that indices of complexity provide unique information independent of the distribution of raw data values.

Differences and similarities among the complexity measures were apparent in the correlation analysis. DFA and ER are theoretically and methodologically distinct approaches that were applied to different aspects (i.e., vertical vs. horizontal structure) of the raw data. Such differences could have accounted for their weak association. Similarly, DFA and ApEn are theoretically and methodologically distinct; yet despite their common application to the vertical structure of the time series, they also were only weakly associated. In contrast, ER and ApEn, as theoretically similar measures applied to different aspects of the raw data, were strongly associated. The result indicated that in the analysis of ambulatory activity data, theoretically similar complexity measures produce similar results.

Importantly, the activity level of participants did not appear to influence *how much* ambulatory activity varied from one minute to the next. Furthermore, the weak and generally insignificant association between CV and each complexity measure supports the fundamental difference in approach between linear and nonlinear measures of variation; linear measures like CV focus on the magnitude of variation in a distribution without regard to the order in which data points accumulate; nonlinear measures of complexity are specifically concerned with the temporal structure of data values (35, 36).

Our findings added to a growing body of literature supporting the clinical utility of nonlinear analytical tools to biological signals (8, 10-15, 35-38). In particular, the study expanded upon previous laboratory gait analyses (22-24, 39) by analyzing walking behavior

recorded during customary activity in natural environments. This distinction highlights the robustness of nonlinear tools like DFA and ER for contributing to the understanding of walking function.

Our study has implications for clinical geriatrics and future gerontological research. We believe that the health promotion benefits of ambulatory activity may be more than providing a vehicle for simply maintaining physiologic capacity (e.g., aerobic fitness, balance, leg strength); increased levels of activity appear to be linked to complex patterns of behavior, which appear paradoxically irregular from minute to minute yet persistent across hours and days. Sedentarism, perhaps somewhat like advanced aging and disease (12-14), appears to be associated with a loss of complexity in the temporal structure of activity patterns, and therefore, with the possibility that chronic inactivity might result in the reduced ability to adapt walking function to various task demands and environmental conditions.

The study was preliminary and had limitations. External factors that might have influenced ambulatory activity (e.g., weather, suitability of outdoor environment, family composition, and accessibility to transportation and indoor walking facilities) were not considered. Furthermore, global physical activity could not be inferred from step counts alone. Some inactive subjects, for example, may have preferred non-ambulatory types of exercise activities such as swimming and weight training. Future investigations should seek to improve upon these issues when attempting to confirm the study findings.

CONCLUSION

The analysis of customary ambulatory activity patterns in community-dwelling older adults revealed complex nonlinear dynamics; greater complexity was associated with higher

levels of activity. The presence of complex ambulatory activity patterns supported the idea that the adaptability of walking behavior to various task demands and environmental conditions is an important feature of healthy aging.

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Appendix 1. ER Computation

To compute the ER, a raw time series was first transformed into a binary sequence of values (i.e., 0 and 1; Figure 1). For each 24-hour period of SW3 recording for a given subject, a binary sequence $X = \{X_i\}$ where $i = 1, 2, ..., 1440$ was generated as follows. From the raw step count time series $S = \{ S_i \}$ where $i = 1, 2, ...,1440$, if S_i *was* larger or equal to 1, the value of 1 was assigned to X_i; otherwise the value of 0 was assigned to X_i. Furthermore, ER differentiates the sequences with the same distribution but with different temporal patterns by calculating conditional probabilities of subsequences with length m from 1 to infinity (15). For our study we used m = 2 which is the "optimal" length size based on the length of our time series and the variance characteristics of the time series similarly with the ApEn calculations (Equation 1).

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INSERT EQUATION 1 ABOUT HERE

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where x is the sequence with length i.

FIGURE LEGENDS

Figure 1. *A*: Representative time series of step counts in 1-minute intervals for a full day obtained from an active individual. *B & C*: Conceptual illustration of the process for transforming representative raw step count time series into a binary sequence of minutes containing activity (1) or no activity (0). The transformation removed the effect of step count values (i.e., vertical structure) in preparation for calculating Entropy Rate.

Table 1: Sample characteristics. Unless otherwise indicated, data are group means (standard deviation). No subject reported using an assistive device (e.g., cane or walker) for walking.

	Highly Active (n = 46)	Moderately Active (n = 86)	Inactive (n = 25)
Age	78.9 (5.7)	80.7 (5.7)	80.2 (6.4)
Male (n)	16	33	15
Female (n)	30	53	10
Body Mass Index	24.9 (4.3)	26.7 (4.2)	27.5 (5.9)
Daily Steps	12660 (2080)	7596 (1314)	3893 (969)
Daily Minutes	400 (30)	300 (23)	189 (14)

Table 2. Group mean (standard deviation) Detrended Fluctuation Analysis (DFA), Entropy Rate (ER), Approximate Entropy (ApEn), and Coefficient of Variation (CV) for daily time series. DFA, ER, and ApEn group means were significantly different from one another ($p<0.01$), while CV group means were not ($p=0.55$).

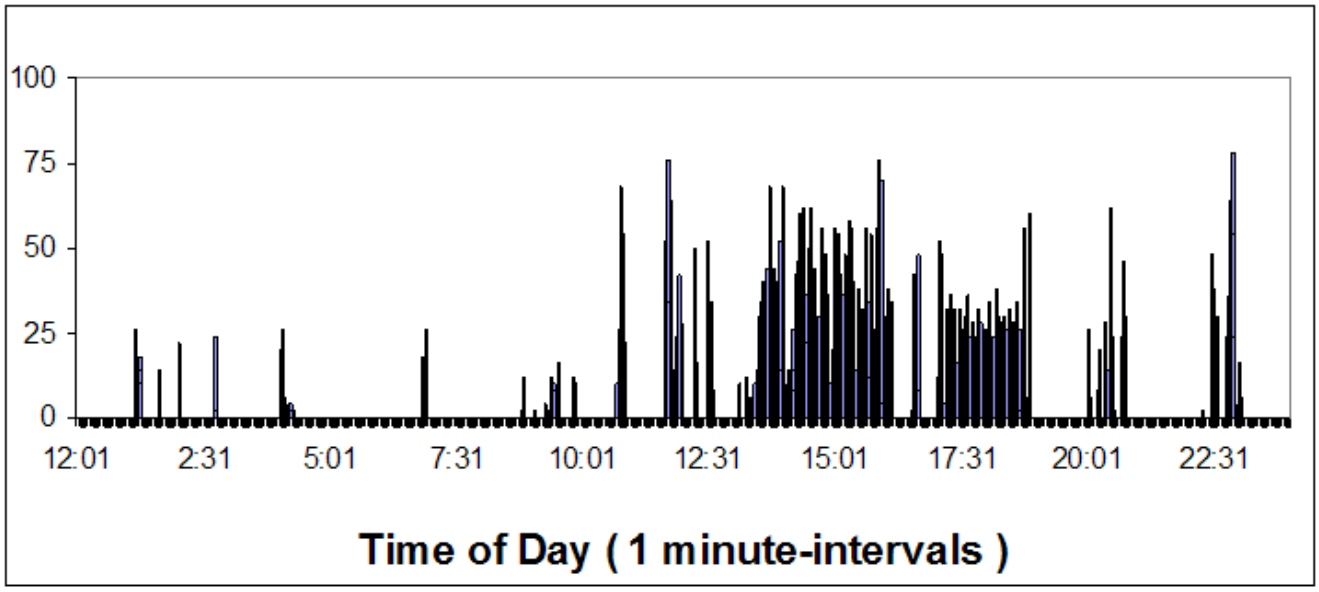
	Highly Active (n = 46)	Moderately Active (n = 86)	Inactive (n = 25)
DFA*	0.88 (0.11)	0.82 (0.08)	0.72 (0.07)
ER**	3.94 (0.39)	3.61 (0.55)	2.89 (0.57)
ApEn***	0.5010 (0.08)	0.4018 ((0.08)	0.2813 (0.07)
CV	92.3 (10.0)	91.2 (8.9)	89.9 (8.0)

*in α values
**parameter m used was equal to 2 (see Appendix 1)
***parameters used were: m = 2, r = 0.2*standard deviation of daily time series values

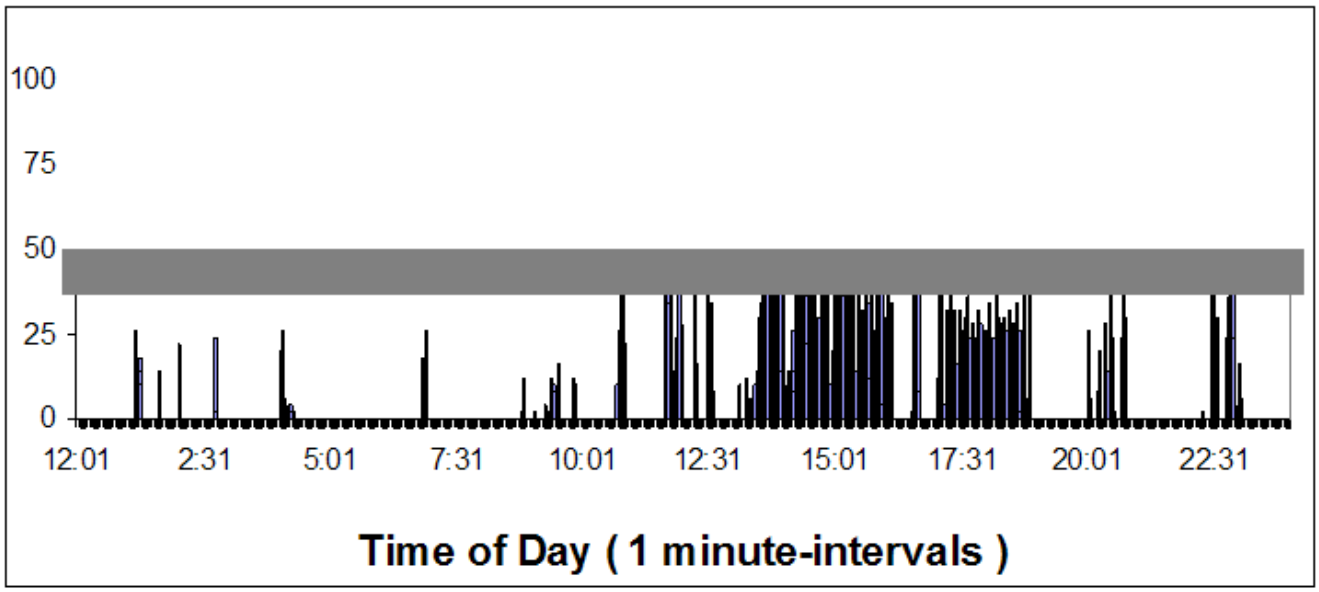
Table 3. Pearson product moment correlations reflecting associations between various combinations of descriptive, nonlinear, and linear measures (n = 157). DFA = Detrended Fluctuation Analysis; ER = Entropy Rate; ApEn = Approximate Entropy; CV = Coefficient of Variation; *p < 0.001.

	Steps	Minutes	DFA	ER	ApEn	CV
Steps	1	0.81 (<0.01)*	0.57 (<0.01)*	0.52 (<0.01)*	0.69 (<0.01)*	0.02 (0.83)
Minutes		1	0.46 (<0.01)*	0.54 (<0.01)*	0.65 (<0.01)*	0.06 (0.44)
DFA			1	0.14 (0.09)	0.22 (0.01)*	0.11 (0.16)
ER				1	0.87 (<0.01)*	0.34 (<0.01)*
ApEn					1	0.15 (0.06)
CV						1

A


100
75
50
25
0
12:01
2:31
5:01
7:31
10:01
12:31
15:01
17:31
20:01
22:31
Time of Day (1 minute-intervals)

B


100
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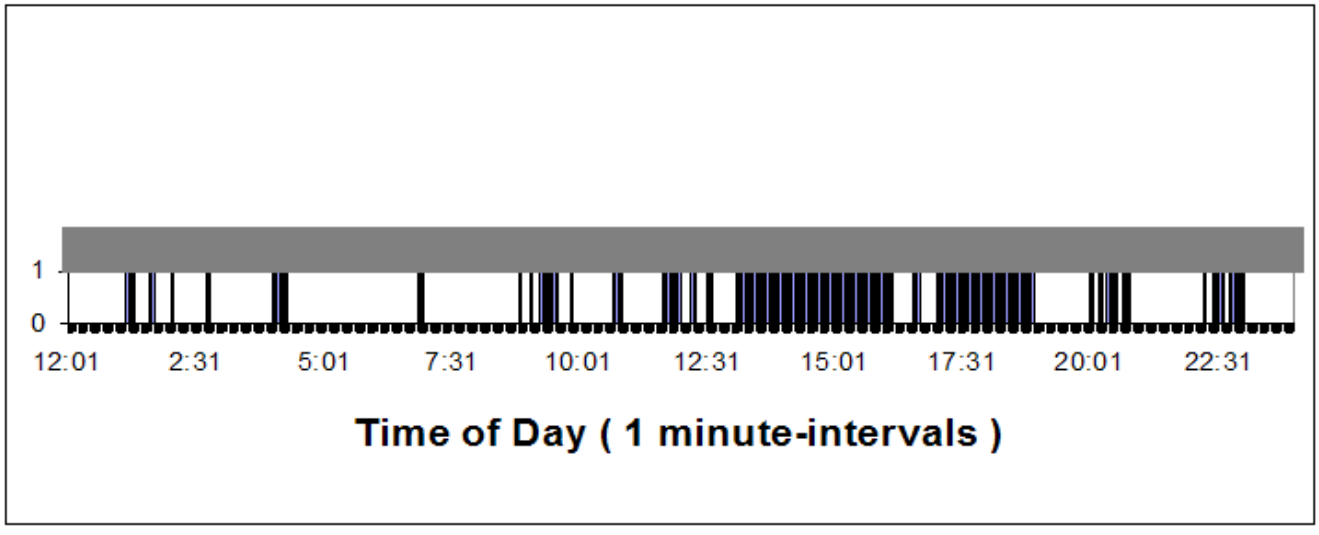
10:01
12:31
15:01
17:31
20:01
22:31
Time of Day (1 minute-intervals)

C


1
0
12:01
2:31
5:01
7:31
10:01
12:31
15:01
17:31
20:01
22:31
Time of Day (1 minute-intervals)

Equation 1. Entropy Rate Calculation from Appendix 1.

$$H(x) = \frac{1}{m} \sum_{x_i \epsilon x} p(x_1, x_2, \dots, x_m) \log p\left(x_i | x_{i-(m-1)}, \dots, x_{i-1}\right)$$