DATA TRANSFORMS FOR SPECTRAL ANALYSES OF HEART RATE VARIABILITY

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ABSTRACT

Autoregressive and fast Fourier transform spectral analyses of high-frequency heart rate variability (HF-HRV) result in exponentially-distributed values that make standard parametric statistical analyses problematic. In this paper, we evaluate three transforms of raw HF-HRV spectral power. Two occur commonly in the literature (a natural log [ln] transform and a reactivity transform); a third is novel (a "percent deviation from the mean" transform). A single data set was used, with each subject providing two data points and for which we predicted a significant difference in HF-HRV power. We quantified the effect size of each transform by noting the percentage of (non)overlap between the ± 1 standard errors surrounding the two period means, with less overlap indicating a stronger effect. Overlap was 19.2% in the raw data (Fig 1b.), 3.7% in the ln transform (Fig. 2b), –57.1% in the reactivity transform (Fig. 3b), and –70.2% in the percent deviation transform (Fig. 4b). The percent deviation transform resulted in more normally-distributed data than the reactivity transform and more tightly-distributed data than the ln transform, making it a favorable choice for investigators.

Keywords: heart rate variability, high-frequency power, spectral analysis, natural log, reactivity

INTRODUCTION

Beat-to-beat changes in heart rate, termed heart rate variability (HRV) are strongly connected with long-term human health and performance [1–3]. Spectral analyses of HRV (via either fast Fourier transform [FFT] or autoregressive methods) are popular and appear frequently in the psychophysiological literature. These analyses involve the decomposition of beat-to-beat variability into underlying frequency components, and derive spectral power (in $ms^2\ Hz^{-1}$) as the area under the spectral density within a specified frequency band. Spectral power within the 0.15 to 0.4 Hz indexes high frequency HRV (HF-HRV) [4, 5].

However, analyzing this "raw" spectral power with standard parametric statistical analyses (e.g., t-tests, analysis of variance, regression) is problematic, because individual scores are not normally distributed. Consider the experimental data presented in Figure 1a. HF-HRV power is plotted for 16 different subjects during two time periods: rest (Period 1) and a working memory task (Period 2). While Figure 1a illustrates that nearly all subjects showed a predicted decrease in HF-HRV from Period 1 to Period 2, the data are exponentially distributed in both periods (Fig. 2a), leading to inflated period means and standard deviations (SDs; see Fig. 1b), and diminishing the size of the effect.

As a remedy for this situation, a number of different data transforms have been applied to HF-HRV data before statistical tests are performed (Table 1). In this paper, we evaluate two common transforms (natural log, reactivity) as well as a novel one, which we term a *percent deviation from the mean*. We evaluate the merits and consequences of each and offer suggestions to future researchers.

METHODS

We performed three transforms of the raw spectral power data shown in Figure 1a. Table 1 details these transforms for a situation in which each subject produces two data points (p_1 and p_2), with resulting data presented in Figures 2–4. We generalize the formulas in Table 1, however, to n number of data points, and later present a comparison of the transforms for a data set in which each subject produces six data points (Figs. 5–8).

A *natural log* (ln) *transform* takes the ln of each raw value. A *reactivity transform* takes the difference between each raw value and each subject's mean raw value. Finally, a *percent deviation from the mean* transform takes the difference between each raw value and the mean of the raw values, dividing the difference by the mean, and multiplying that by 100.

The reactivity and the percent deviation transform result in p_1 and p_2 values that are of equal magnitude but opposite sign. They could just as well be calculated to produce a single reactivity score or percent deviation score per subject. The method we chose, however, facilitates comparison with the raw data and ln transform, and also generalizes to experiments with more than two data points per subject.

For each subject producing n unique data points, let $avg(p_1 : p_n)$ be the average of data points p_1 through p_n.

Transform	**Period 1 value**	**Period 2 value**	**...**	**Period *n* value**
[Raw]	p_1	p_2	...	p_n
Natural log	$\log_e(p_1)$	$\log_e(p_2)$	...	$\log_e(p_n)$
Reactivity	$p_1 - avg(p_1 : p_n)$	$p_2 - avg(p_1 : p_n)$	...	$p_n - avg(p_1 : p_n)$
Percent Deviation	$\frac{p_1 - avg(p_1 : p_n)}{avg(p_1 : p_n)} \times 100$	$\frac{p_2 - avg(p_1 : p_n)}{avg(p_1 : p_n)} \times 100$	...	$\frac{p_n - avg(p_1 : p_n)}{avg(p_1 : p_n)} \times 100$

Table 1. Comparison of transforms. p_1 and p_2 represent an individual subject's raw values for Periods 1 and 2, and so on.

RESULTS

We plot both the individual data points from each transform (Figs. 2a, 3a, 4a) as well as period means and ± 1 standard errors (Figs. 2b, 3b, 4b). A standard error (SE) is calculated as $[\,\mathrm{SD} / \sqrt{\text{number of subjects}}\,]$. Across the different transforms, individual subjects are labeled with a fixed number so that they can be tracked. As an index of the size of the effect, we calculated the percentage of (non)overlap between the error bars:

$$\frac{(\mathrm{mean}_2 + \mathrm{SE}_2) - (\mathrm{mean}_1 - \mathrm{SE}_1)}{(\mathrm{mean}_1 + \mathrm{SE}_1) - (\mathrm{mean}_2 - \mathrm{SE}_2)} \times 100\,. \tag{1}$$

Less overlap means a greater difference between the period 1 and 2 data. Overlap was 19.2% in the raw data (Fig 1b.), 3.7% in the ln transform (Fig. 2b), –57.1% in the reactivity transform (Fig. 3b), and –70.2% in the percent deviation transform (Fig. 4b).

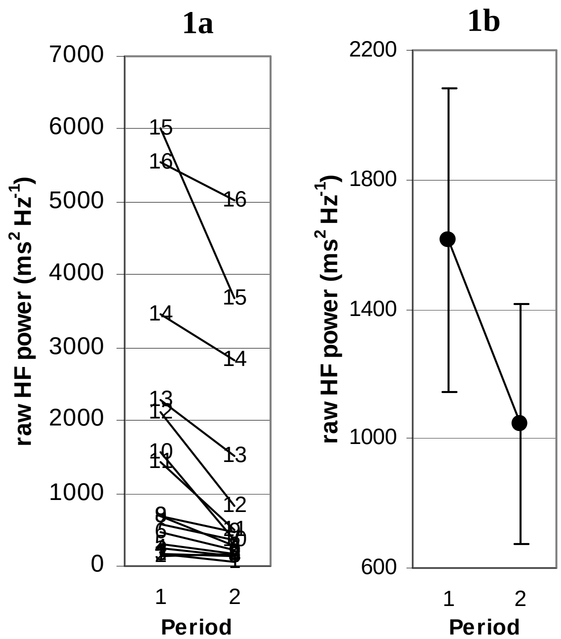


Figure 1a. Raw HF-HRV data for 16 subjects.
Figure 1b. Means and ± 1 SEs for the data in Fig 1a.

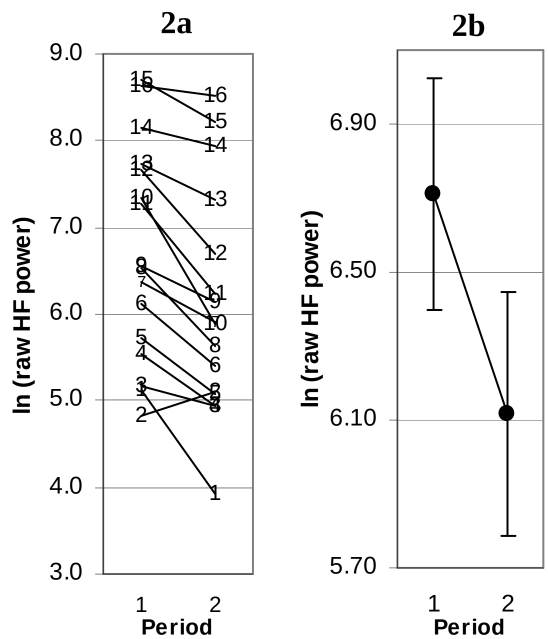


Figure 2a. ln transform of the raw data.
Figure 2b. Means and ± 1 SEs for the data in Fig 2a.

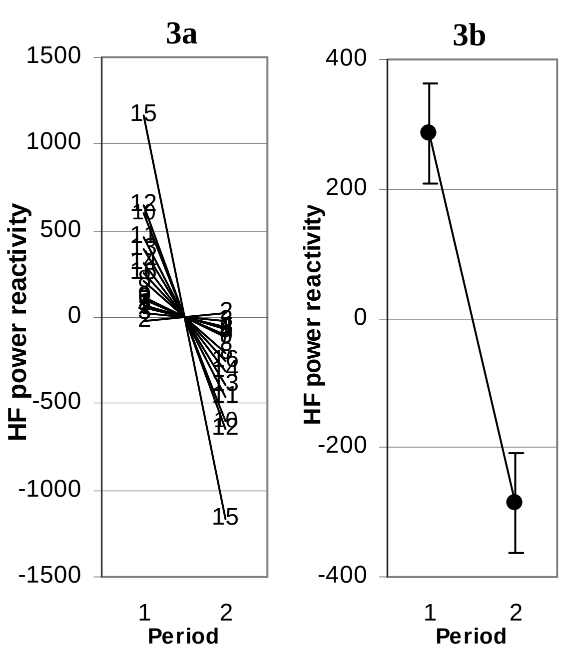


Figure 3a. Reactivity transform of the raw data.
Figure 3b. Means and ± 1 SEs for the data in Fig 3a.

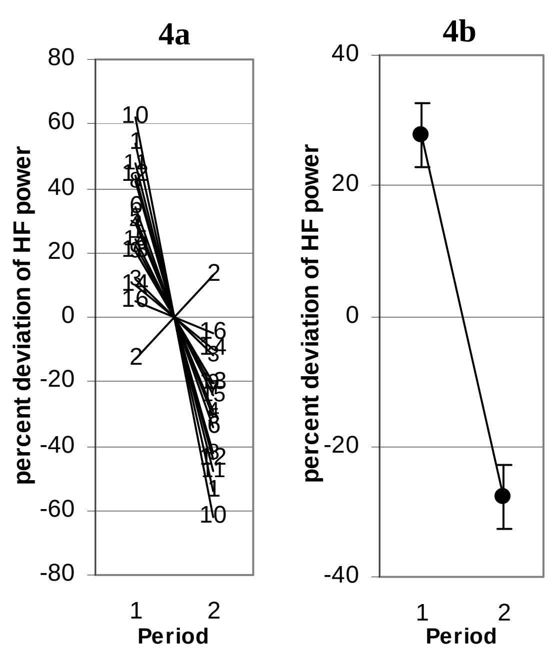


Figure 4a. Percent deviation transform of the raw data.
Figure 4b. Means and ± 1 SEs for the data in Fig 4a.

The raw data in Figure 1 were actually from a larger data set, shown in Figure 5. HF power was measured for six periods (three in a “White Light” condition and three in a “Red Light” condition) for the same 16 subjects above (p_1 and p_2 data points in Fig. 1a correspond to Periods 1 and 2 of the Red Light condition in Fig. 5). Period means and ± 1 SEs are shown. As with the first analysis, the largest error bars appear in the raw data (Fig. 5), and the smallest in the percent deviation transform (Fig. 8).

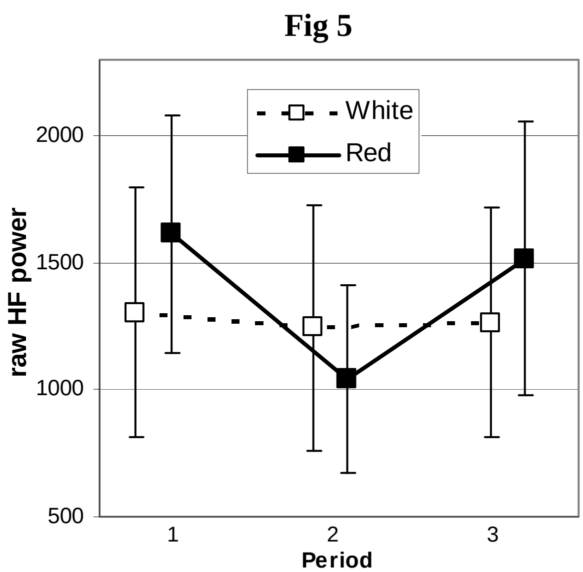


Figure 5. Raw HF-HRV data.

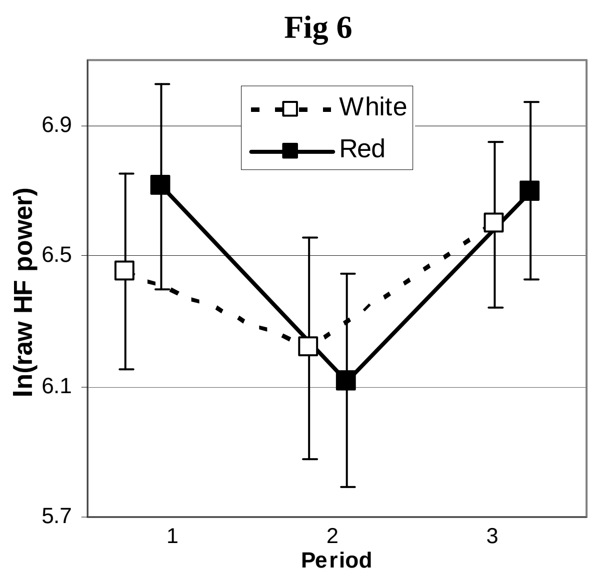


Figure 6. ln transform.

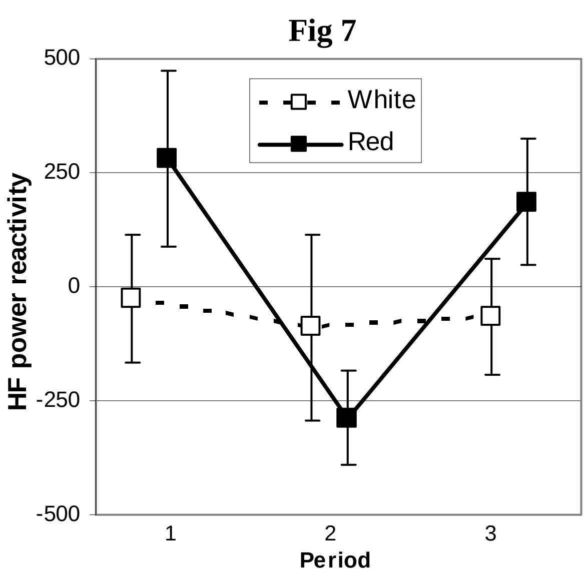


Figure 7. Reactivity transform.

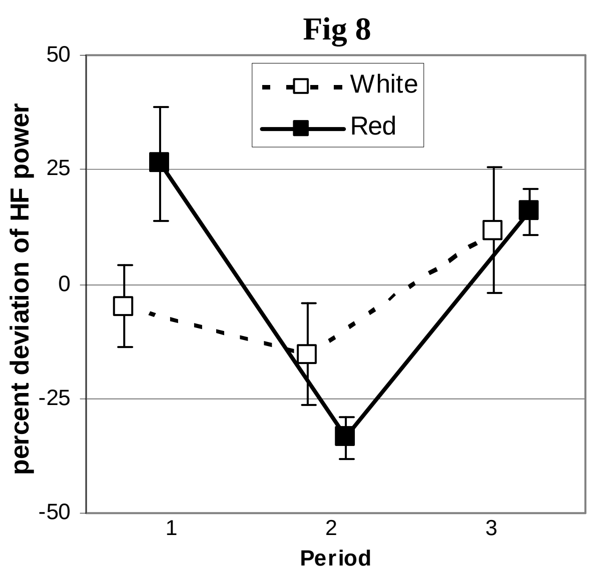
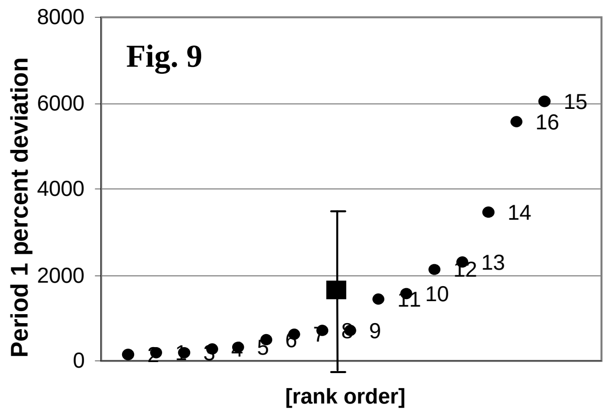


Figure 8. Percent deviation transform.

Finally, Figures 9–12 reproduce, respectively, individual Period 1 data points from Figures 1a, 2a, 3a, and 4a, rank ordered by ascending magnitude. The mean and standard deviation of those data points are plotted in each figure.



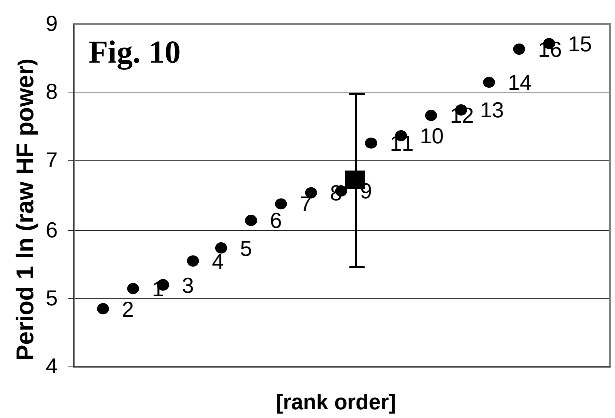
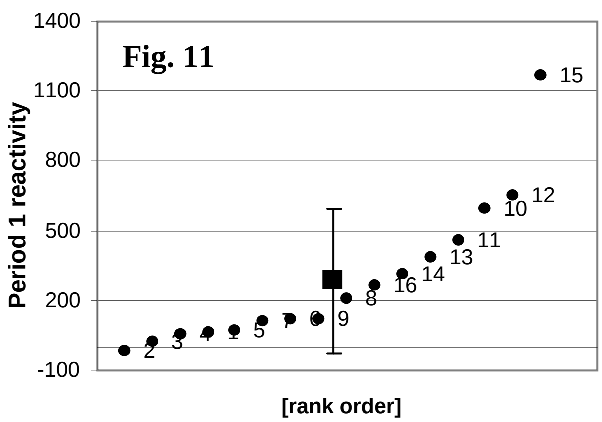


Figure 9. Raw HF power values for Period 1, ordered by magnitude.
Figure 10. ln transform of raw values for Period 1, ordered by magnitude.



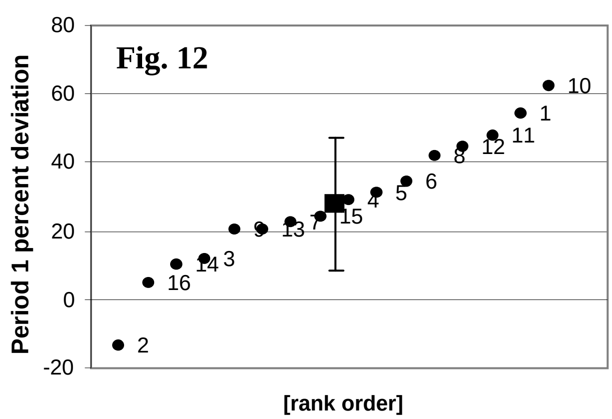


Figure 11. Reactivity transform of raw values for Period 1, ordered by magnitude.
Figure 12. Percent deviation transform of raw values for Period 1, ordered by magnitude.

DISCUSSION

While the ln transform results in a more normal distribution of data points (Fig. 10) than the raw HF power (Fig. 9), the standard errors for the ln transform are still relatively large (Fig. 2b), decreasing the size of the effect.

Second, while the reactivity transform shows a major improvement compared to the ln transform, data are *not* normally distributed (Fig. 11): a few subjects possessed large reactivity values (specifically, those with high Period 1 raw values). These high values have the potential to inflate the difference between Periods 1 and 2, leading to a potentially false positive result.

By contrast, the percent deviation transform results in more normally-distributed data (Fig. 12), than the reactivity transform (Fig. 11). Additionally, it produces data that are more tightly distributed (Fig. 4a) than the ln transform (Fig. 2a), resulting in smaller error bars. Thus, the percent deviation transform emerges as the strongest candidate for further use.

Next, we discuss the findings shown in Figures 5–8. Visual inspection clearly reveals that the percent deviation transform (Fig. 8) once again resulted in the smaller error bars than any other transformation. Thus, not only does the percent deviation transform result in normally-distributed data points (Fig. 12), but it also generalizes to analyses with a larger number of data points per subject (in this case, 6), furthering its utility.

CONCLUSIONS

We demonstrate here that different simple transforms of HF-HRV data can lead to dramatic differences in the observed size of an effect. This finding echoes an infrequently-cited report from some 40 years ago, which developed a similar conclusion from cardiorespiratory data [6]. Which data transformation (if any) to use is an important consideration that is often neglected in reporting results. We offer the present findings as an illustration (and potential solution) to this problem for spectral analyses of HRV.

While ln and reactivity transforms are often applied before statistical analyses are performed, neither possesses the benefits of the percent deviation transform that we introduced here. The percent deviation transform resulted in more normally-distributed data than the reactivity transform, and more tightly-distributed data than the ln transform; these jointly decrease the chance of either a false positive or a false negative result, respectively.

ACKNOWLEDGMENTS

This research was conducted with partial funding by the American Institute of Architects College of Fellows Latrobe Fellowship to Eve A. Edelstein.

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