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FRONT MATTER: COMMENT

Fractal analysis of thermoregulatory complexity

Comment on: Blessing W, Ootsuka Y. Timing of activities of daily life is jaggy: How episodic ultradian changes in body and brain temperature are integrated into this process. Temperature 2016; 3:371-83; http://dx.doi.org/10.1080/23328940.2016.1177159

If all you have is a hammer, everything looks like a nail.
Abraham Maslow, The Psychology of Science (1966)

Blessing and Ootsuka present in this issue of *Temperature*[1] a cogent treatment of the analytical and conceptual pitfalls of 2 heavy hitters in physiology and behavior: the concept of homeostasis and the concept that most biobehavioral outcomes of a rhythmical nature are intrinsically sinusoidal and thus imbued with predictable periodicity. These conventions, the authors argue, fail to take into account the unpredictable but real patterns of jaggedness of manifold time-varying biobehavioral variables, and this failure raises a substantial barrier to progress in the physiological and behavioral sciences.

Homeostasis is of such fundamental conceptual, explanatory and predictive importance in the biobehavioral and biomedical canons that to question its virtue is to invite marginalization by the gatekeepers of proper thought. Such pertains as well to the long tradition of seeking periodic sinusoidal descriptions of the fluctuations elaborated by manifold biobehavioral outcomes. Indeed, Blessing and Ootsuka note the hostility evinced by referees in prior attempts to publish analyses that depart from the homeostatic and sinusoidal conventions.

The historical roots of homeostasis, nicely detailed by Blessing and Ootsuka, can be distilled, imperfectly, into 2 words: averaging and engineering. Because many “homeostatic” variables measured via the relatively crude means available to classical physiologists were recorded as averaged values, any inherent jaggedness tended to be smoothed into oblivion. Hence variables such as core temperature tended toward a guise of stability. The level at which that occurred was, of course, a function of experimental manipulations or naturalistic conditions. That source of variation, in turn, came to be viewed through the lens of engineering control theory with its immensely influential protocol of negative feedback summation with a reference set-point as a means of actuating effector responses that stabilize the controlled output at some desired level. Moreover, an influential aspect of the typical physiologists’ understanding of homeostatic control was (and remains) the reductive pedagogical simplification of control system dynamics into flattened steady-state static analyses or simplistic heuristic descriptions in the coursework aimed at physiology students not versed in the complex number plane, Laplace transforms and related mathematics needed to appreciate the surprisingly rich dynamics of even fairly elementary control systems. Not incidentally, the classical mathematics of control theory depends on the frequency domain, a realm in which sophisticated sinusoidal transformations of time domain signals make system solutions more tractable.

Similarly, in chronobiology the classical mathematics of sinusoids, notably Fourier analysis, emerged as an immensely useful means of decomposing time varying signals into sums of sinusoids to discern patterns of regularity. On broad time scales, e.g., days, weeks and years, many biological outputs are time-varying outcomes that indeed are amenable to analyses aimed at identifying regularity. Body temperature and metabolic rate are but 2 outcomes that exhibit a circadian predictability in which peaks and nadirs recur daily; in hibernating mammals feeding behavior and fat storage exhibit circannual predictability wherein peaks and nadirs recur annually. However, representing a time-varying outcome as a sinusoid, another instance of smoothing, diverts attention from finer grained ultradian fluctuations when these are revealed by modern biometric devices. Modern technology reveals high frequency signal fluctuations in exquisite detail for outcomes such as core and brown adipose tissue temperature, metabolic rate (using continuous calorimetry), for measures of cardiovascular function such as heart rate and blood pressure, and for a variety of behavioral outcomes such as bouts of feeding and activity. Blessing and Ootsuka write that ultradian biobehavioral signals are inherently stochastic and provide a sound basis for this conclusion, yet explain that important biobehavioral information can be teased out of the complexity. To do so entails the application of fractal analysis.

The term 'fractal,' coined in 1975 by Benoit Mandelbrot (see ref. 2), derives from the Latin adjective *fractus*, meaning fractured or broken. Of particular importance to Blessing and Ootsuka is the notion that the irregular spiky geometry of a signal of interest (say brown adipose tissue temperature) can be described in terms of a fractional dimension, which unlike a geometric dimension, has a non-integer value. Thus, whereas the dimension 1 corresponds to a straight line and the dimension 2 corresponds to an area, a fractional (specifically a Higuchi fractional) dimension has a non-integer value. I leave the computational details of the Higuchi fractional dimension to Blessing and Ootsuka (who provide good references for readers seeking a better understanding), but the bottom line is simple: the fractional dimension is a measure of a signal's complexity. Thus, a value of 1.1 might correspond to a simple cosine wave, a value of 1.3 to a jagged brown adipose tissue temperature signal, while a value approaching 2 corresponds to a completely random signal.

Processing a complex signal for quantification of the fractal dimension involves use of wavelet mathematics,[3] and particular emphasis is placed on the discrete wave transform as this extracts a signal's salient features in an efficient manner.

Why evaluate the complexity in terms of wavelets and fractional dimensions? When chronobiologys' conventional methods for identifying regularity are applied to complex stochastic signals, the interrogation risks making the data confess to something it is not guilty of. By contrast, fractal analyses of complexity have a burgeoning record of practical, explanatory, predictive and prognostic value in many fields; e.g., image analysis, acoustics, economics, geoscience, neuroscience and metabolism. A well-known example is that lower complexity in the form of reduced heart rate variability predicts a greater risk of sudden cardiac death.[4] Lower heart rate variability is also associated with obesity, diabetes and a variety of other disease states.[5]

Modern methods for obtaining and analyzing continuous measurements of metabolic and behavioral variables of particular importance to thermoregulation and its allied disciplines such as body fuel regulation offer a wealth of opportunity for discovering the significance of metabolic and behavioral complexity in health and disease.

References

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