Bios Data Analysis. Part 10.
Process Entropy, a Multidimensional Measure of Diversity and Symmetry

H. Sabelli, M. Patel, A. Sugerman, L. Kovacevic and L. Kauffman
Chicago Center for Creative Development
University of Illinois at Chicago
2400 Lakeview
Chicago, IL 60614
e-mail: Hector_Sabelli@rush.edu
web-page: www.creativebios.com

Abstract: Process entropy is a set of techniques to study the statistical entropy of creative processes. Measuring the entropy of time series by epochs shows aperiodic rises and falls in many empirical time series (galaxy distribution, heartbeats, DNA, economic data), some stochastic series, and mathematical bios; random and chaotic series show steady values. In recursions, entropy increases from steady state equilibrium to periodicity to chaos to bios to infinitation, with a relative decrease during bios. Measuring entropy as a function of bins shows that entropy increases with symmetry and diversity in the data (not disorder, decay, or complexity). Entropy does not measure disorder because it is maximal in ordered series, not in random data. Entropy does not measure decay, because cardiac illness and aging decrease entropy of heartbeat intervals. The entropy of higher-dimensional components (measured with the recurrence method) is higher in biological, economic, and meteorological series than in their randomized copies; it is associated with order but it does not correlate with complexity. These results are compatible with Carnot's notion of asymmetric but bi-directional interconversion of ordered action and disordered flux of energy, but not with Clausius' formulation of entropy maximization as disordering.

Keywords: bios, chaos, complexity, creativity, diversity, entropy, evolution, galaxies, heart rate variation, information, process theory, recurrence, thermodynamics.

1. Introduction

Measures of entropy have been found useful in many fields. A large number of entropy measures have been introduced, some of them intended to quantify the complexity of organization (e.g. Kolmogorov-Sinai entropy). This article presents *process entropy*, a method for measuring the entropy of creative processes. This requires examining its change in time, and considering both simple and complex components of organization. To consider processes, it measures the statistical entropy of time series rather than of states. To consider creative phenomena, it considers simple and complex components by also examining differences and embeddings. To interpret the meaning of measurements, it examines the results obtained with empirical and mathematical series.

The usual assumptions of statistical mechanics do not apply to the entropy of processes, because they are designed to model the thermodynamic entropy of states at one time, and they refer only to the distribution of particles and not to organization in multiple levels of complexity. A measurement of the entropy of creative phenomena is particularly necessary because the concept of entropy as disorder advanced by standard thermodynamics contradicts the notion of creative evolution. A number of solutions have been proposed for this contradiction; physicists have proposed mechanisms for reducing entropy [Schrödinger

(1945); Prigogine (1980, (1997); Layzer, D. (1967)], while biological thinkers [Lotka (1922); Black (1978); Brooks and Wiley (1984)] have proposed that evolution results from the increase in entropy. In any case, there are no methods to measure the entropy of creative phenomena. These basic issues motivate the development of a new approach to the measurement of the entropy of evolving processes.

Definition of entropy: The term entropy, meaning in Greek transformation, has been given many different and contradictory definitions [Bunge (1986); Corning and Kline (1998)]. Currently, many authors use the term to mean disorder, while many others regard entropy as a measure of complexity (e.g. of an ecological community). There are three distinct types of meanings of the term entropy:

(1) Physical: Carnot discovered that the transformation of work into heat is greater than the transformation of heat into work. Friction produces heat. This concept of bi-directional and asymmetric transformation was later changed into the notion of unidirectional decay of energy by Clausius. Thermodynamics defines the change in entropy

$$\mathbf{dS = dQ/T},$$

where dQ is the flow of heat and T is the absolute temperature. The second law postulates

$$\mathbf{dS \geq 0}.$$

Only changes in entropy can be measured; entropy itself cannot. The definition applies to the idealized case in which the change in Q does not produce a change in temperature (thermodynamic paradox). The physical concept of entropy has been extended to include related properties. For instance, Hawkings define the entropy of a black hole as its surface [Thorne (1994)]. The physical concept of entropy refers to the uniformity of distribution of values, regardless of the quantities measured.

(2) Mathematical: Before the thermodynamic concept of entropy was developed, de Moivre described the equation

$$\mathbf{H = - \sum P_i \log (P_i)},$$

where P_i is a probability or expectation. This equation measures the regularity of a distribution in a histogram: when there is an equal number of data points in each bin, H is maximal. H has no intrinsic dimension.

To eliminate the contradiction between mechanics, which describes conservative, time reversible processes, and the thermodynamics of closed systems that posits irreversible change, Boltzmann adopted de Moivre's equation to account for thermodynamic entropy by the distribution of particles and velocities. According to this model, the thermodynamic entropy is measured by the logarithm of the number of microscopic states that can generate the same macroscopic appearance. The Boltzmann equation

$$\mathbf{H = - k \Sigma P_i \ln(P_i)}$$

adds to the de Moivre equation a constant k that has the dimensions of change in heat over temperature. In contrast to thermodynamic entropy S, statistical mechanical entropy H is in principle measurable. Also, while the expansion of a gas filling a small closed container increases when it is allowed to expand and fill a larger container, the entropy of these two random distributions is the same (statistical mechanics paradox). In statistical mechanics, irreversibility is accounted for by the low probability of organization emerging out of disorder. Yet, one cannot logically base thermodynamics on statistical theory and then exclude the improbable from occurring – a theorem demonstrated by Poincaré establishes that any closed system must return eventually to its original state. Gibbs, Planck, Zermelo, and many other leading thinkers, with solid arguments that remain unanswered, have rejected the statistical explanation of thermodynamics accepted by most contemporary physicists.

Shannon [(1964)] adopted the de Moivre equation to measure the probability of the occurrence of a signal as a definition and measure of information. Notwithstanding, many authors, quoting Shannon but adhering to the standard Clausius-Boltzmann interpretation of entropy as disorder, define information as negative entropy. In any case, entropy measures only one aspect of information, namely the amount being transmitted, disregarding its meaning, its generation, and other essential aspects of information. This was explicitly stated by Shannon. Information can be lost but it cannot be generated during transmission through wires; the notion that information can be lost but not generated in the universe at large does not follow.

The relation between informational and thermodynamic entropy is still being questioned, particularly because probability involves a potential for reversibility. Although P_i is interpreted as a probability, it is possible to measure the entropy of any distribution, whether determined or stochastic. Mathematical entropy can be embodied physically in many different ways, such as a surface area as in the case of black holes. Instead of viewing statistical entropy as a model for thermodynamic entropy, we may regard thermodynamic, informational and statistical mechanical entropies as particular embodiments of mathematical entropy.

(3) Philosophical: Outside the context of thermodynamics, entropy is largely a metaphor, one that in fact has been stretched far beyond its breaking point [Cohen and Steward (1994)]. Entropy has become a popular word implying any type of disorder, disorganization, waste, or uncertainty. Clausius and Boltzmann, based on closed system models, portrayed the maximization of entropy as decay towards equilibrium, rest and disorder. Elementary texts appeal to purportedly intuitive examples –e.g. glasses break but they never spontaneously form. This neglects the fact that glasses must have been formed before they can be broken. The notion of monotonic decay implies that the universe started in a state of maximal organization. It also contradicts the evidence provided by evolution; it has therefore been questioned since the nineteenth century [Engels (reprinted 1940)] up to our times [Gal-Or (1972); Georgescu-Roegen (1971)]. Moreover, the identification of entropy with disorder is meaningless without an independent definition of order. Alternative interpretations include chance, uncertainty, complexity, and diversity [Wicken (1987), (1989)]. According to Yates [(1987)], thermodynamic entropy corresponds to macroscopic symmetry. Some high school textbooks define entropy as the ease with which an arrangement can be disorganized; this implies that entropy is minimal for random configurations, in direct contradiction to statistical mechanics. Echoing philosophical idealism, leading physicists such as Born and Gell-Mann [(1994)] attribute thermodynamic irreversibility to "ignorance." Von Neumann advised Shannon to call his measure of information entropy because "nobody knows what entropy is." This confusion in terminology reflects conceptual uncertainty. One way to resolve this morass of interpretations is to look directly at the mathematical equation that defines entropy, and at the results of empirical measurements.

2. The contradiction between evolution and thermodynamics

Clausius' notion of decay towards disorder and rest contradicts evidence for cosmological change and evolution. It is also at variance with the notion of biological evolution from simple to complex. To reconcile biological evolution and thermodynamics, Schrödinger [(1945)] explained the development and maintenance of life as the result of a local reduction in entropy. He proposed that organisms feed on negative entropy taken from their environment. Prigogine [(1980), (1997)] extended this hypothesis to all dissipative structures, which he regards as far-from-equilibrium, open systems that reduce internal entropy by importing free energy from the environment, and exporting entropy to it as heat and waste. There is as yet no empirical data demonstrating that entropy decreases in far-from-equilibrium processes in biological organisms, or in dissipative structures. Moreover, energy flux density is much greater in complex systems such as the brain and the body of organisms than in simple systems such as planets and stars [Chaisson (1987)]. Can complex organisms combine high entropy production with low entropy levels? Actually, radiation and the circulation of matter carry information. What is waste for one species is food for another –oxygen and carbon dioxide are paradigmatic examples. Cycling is prominent in the metabolism of organic matter in the biosphere. Organic matter does not decay to elementary atoms or elementary particles. It is recycled. Similarly, atoms do not decay to quarks but built up larger atoms in the core of stars and molecules elsewhere. Entropy reduction in biological organisms, if any, may thus require processes beyond radiation and elimination.

3. Process entropy

Process entropy is a method to investigate creative transformations by quantifying changes in entropy in successive epochs of time series, and by examining each time series in multiple dimensions constructed by differencing or embedding. Process entropy differs conceptually from other measures of entropy:

- Process entropy measures the statistical entropy of time series, not of a distribution of entities at one instant of time. In this manner, one investigates temporal order, which is the most fundamental type of order (see Part 3) Temporal order is *not* taken into account in standard measurements of statistical entropy (a time series and its shuffled copy have the same entropy), or in the thermodynamic definition of entropy as a state function. However, only changes in thermodynamic entropy can be measured. Correspondingly, process entropy examines changes in statistical entropy.

- Process entropy considers both simple and complex components of variation from a single numerical series by examining a wide range of dimensions across which to measure entropy. In contrast, other methods portray simple and complex components by a single value of entropy. Statistical mechanics, for example, measures the distribution of particles and velocities, but it does not consider complex levels of organization. To measure the entropy of the time series itself is not sufficient. In order to understand a message, we combine letters into words, rather than studying the individual letters.

- The process method interprets the meaning of entropy by examining results obtained in empirical measurements rather than on theoretical grounds. Empirical studies of the statistical entropy of physiological and economic time series [Carlson-Sabelli et al (1996); Sabelli (1989), (1994); Sabelli and Carlson-Sabelli (1999); Sabelli et al (1990), (1994), (1995)] led us to propose that entropy measures *both* symmetry and diversity [Sabelli et al (1994), (1995)].

4. Methods and results

Process entropy measures statistical entropy with the de Moivre equation, used as the definition of entropy in statistics, statistical mechanics and information theory. P_i is interpreted as the relative frequency of a given value (not necessarily a probability). Whenever one bin is empty, $P_i \log_2 (P_i)$ is computed as 0. In this paper, the de Moivre equation is applied to measure (1) the entropy of successive epochs of a time series; (2) the entropy of the differences between consecutive terms of the series; and (3) the entropy of consecutive recurrence of isometric vectors of N successive terms at various embeddings (recurrence entropy). The time series examined in this article and the recurrence method are described in previous parts of this series of articles.

4.1 Entropy by epochs: nonlinear changes in entropy

The entropy of processes, that is changes in entropy, is examined by dividing the time series into epochs and calculating the entropy of each epoch, in an effort to detect changes. We do *not* choose stationary epochs. Random or chaotic series do not show variations in entropy (figure 1). As expected, entropy waxes and wanes in nonperiodic fashion for nonstationary series such as heartbeat intervals, galactic distances, DNA base sequences, economic data, stochastic series, and mathematical bios (figure 1). The entropy of the distribution of galaxies varies in nonlinear manner in space (right ascension) and time (redshift) (figure 2). Entropy also shows nonlinear fluctuations in cellular automata, and in some of them it consistently increases with increasing order [Wolfram (1983)]. Apparently, the selection of stationary data solely accounts for data that support the monotonic order expected by the postulated maximization of thermodynamic entropy. Prigogine accounts for variation by stating that the entropy of an entity is the sum of the endogenous entropy plus the entropy gained (or lost) to its environment. Thus, entropy always increases for the total system, but it may locally decrease.

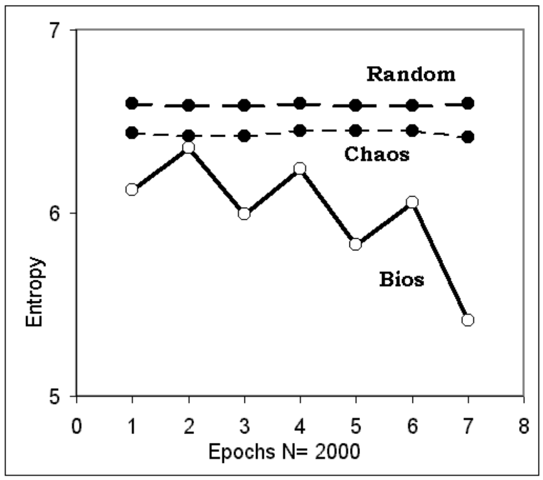

Figure 1: Nonlinear changes in statistical entropy (2000 term epochs) of random data, and of chaotic and biotic series generated by the process equation. The entropy of random and chaotic data does not change across epochs, but biotic series show significant variation.

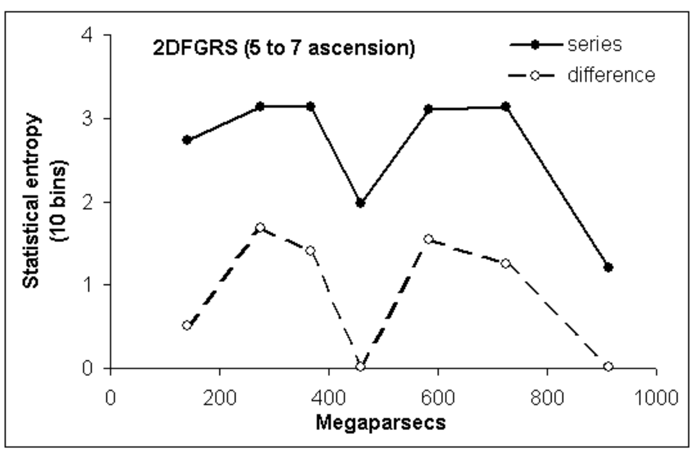

Figure 2: Nonlinear changes in statistical entropy (1000 term epochs) of galaxy redshifts recorded in a narrow range of declinations in the 2DFGRS [Colless (1999)].

4.2 Order and shuffling, simplicity and complexity

Figure 3 presents some simple experiments that show that statistical entropy does not measure disorder or complexity. The statistical entropy of a sequence of consecutive integers (1, 2, ...1000) is larger than the entropy of a uniform random distribution with the same range (figure 3, left) because complete uniformity is not likely to be achieved randomly. This is at variance with the notion that entropy measures disorder. This result may appear trivial, but it is widely held that Shannon's entropy is a measure of randomness [Ebeling et al (2002)]. Comparing progressively more complex series generated by the addition of sine waves shows that entropy can vary nonlinearly as a function of complexity (figure 3 right).

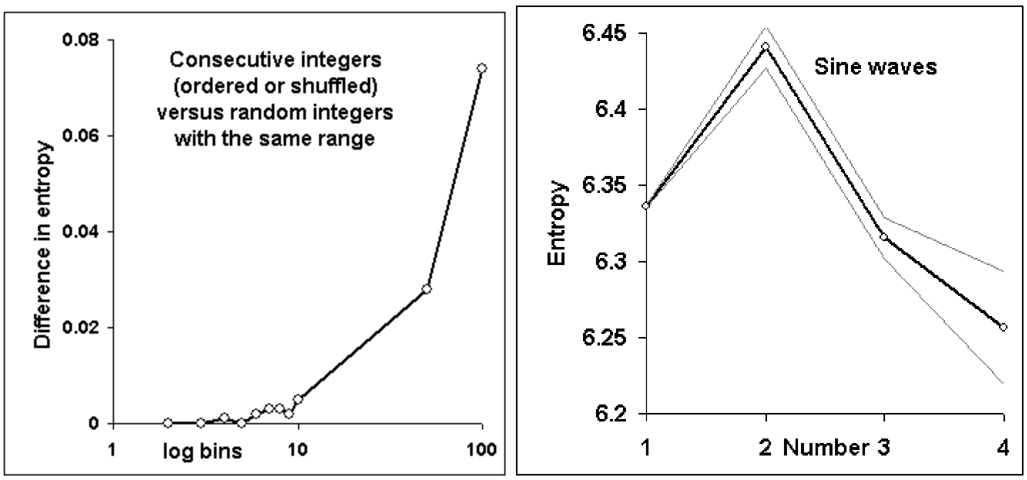

Figure 3: Left: The entropy of a sequence of consecutive integers (1 to 1000) minus the entropy of randomly chosen integers between 1 and 1000. Entropy is measured with 2 to 100 bins (plotted in the x axis using a logarithmic scale). Right: The entropy (mean $\pm$ standard error) of sine waves (N=2000), sums of two, three and four out of phase sine waves, computed with 100 bins.

The overall statistical entropy of a time series is not associated with sequential order. As expected, the entropy of any series is identical to the entropy of its shuffled copy. Statistical entropy is equally low in random or ordered series of two numbers, and it is equally high for distributions of many values, whether randomly distributed or in any kind of pattern.

4.3 Bin variation to measure symmetry and diversity

The value of entropy increases with the number of bins used for its calculation (figure 4), just as the amount of information received depends on the discriminatory power of the receiver. Varying the number of bins (e.g. 2 to 100 bins) allows one to deconstruct entropy into two components: symmetry s and diversity d (figure 4). Entropy H is, within limits, a linear function of the logarithm of the number of bins:

$$\mathbf{H = s + d^* \log_2 n}$$

where n is the number of bins used to calculate entropy, diversity d is the slope, and s is the value at 2 bins (the least number of bins required for the calculation of entropy). Both s and d vary from 0 to 1.

The intercept s depends on the symmetry of the data. It is 1 for all symmetric distributions (random, sinusoidal, chaotic, etc), and varies for economic and physiological data, which manifest various degrees of asymmetry (H < 1 at 2 bins). Asymmetry is also present in biotic series generated by the process equation and in random walks. This is meaningful in view of the asymmetry of time and of other fundamental processes (see [Haldane (1960); Clynes (1969); Corballis and Beale (1976); Sabelli (1989) and also Part 3].

The slope d of the entropy/bin curve increases with the number of different values in the data. The slope is 0 for numerical series with two equally probable values, regardless of their temporal arrangement (random or periodic), and it is 1 for random, sinusoidal, chaotic, biotic series and stochastic series noise (random walks, pink noise). Cardiac R-R intervals, and many other empirical time series (figure 4) have a near 1 slope.

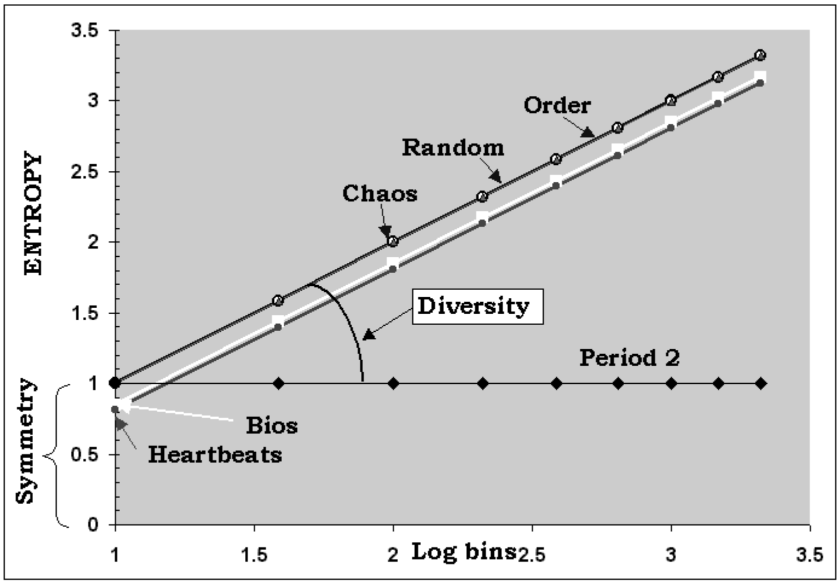

Figure 4: Entropy-bin plot shows the calculation of symmetry (value of entropy at 2 bins, $\log_2 2 = 1$) and diversity (slope). Biotic series have a certain degree of asymmetry. Chaos, random, ordered series, and period 2 are totally symmetric. Note: Lines for chaos, random, and ordered series practically overlap.

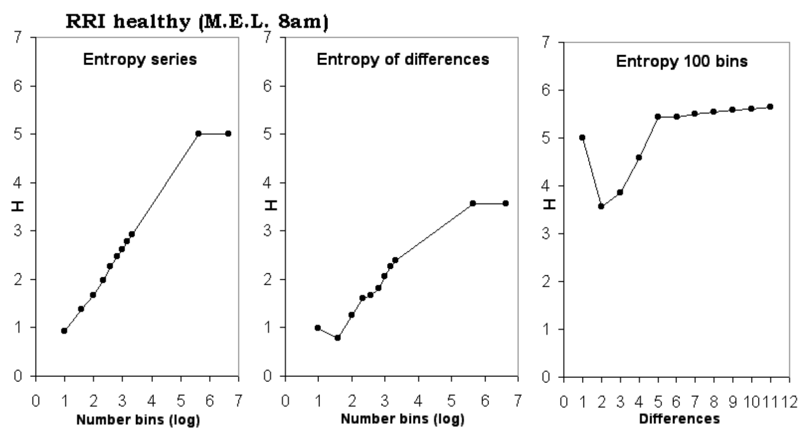

Figure 5: Entropy of heartbeat interval series. Left: Entropy of the time series as a function of the number of bins used for its measurement. Middle: Entropy of the time series of differences between consecutive terms as a function of number of bins. Right: Entropy measured with 100 bins for the time series (1), the time series of differences between consecutive terms (2), the difference of the differences (3), etc up to 10 differences

4.4 Entropy of differences

Measuring the statistical entropy of differences between consecutive terms, the difference of the differences, etc, up to 10 differences, we noted nonlinear changes in empirical series such as those illustrated in figure 5. The entropy of the differences between successive members is lower than the entropy of the time series for cardiac intervals, for integer biotic series, for random walks generated with a small number of steps, for some samples of pink noise, and for periodic and chaotic series. In contrast, the entropy of differences is as high as that of the time series for random numbers, for most statistical noise, and for non-integer mathematical bios. The plot of the entropy of differences versus the number of bins reveals oscillations in many time series, not present for the entropy of the time series itself. Oscillations in difference series are particularly noticeable in some economic data and in heartbeat data from psychotic patients.

4.5 Recurrence entropy

Sequences of consecutive recurrences are arranged in bins according to the length of the sequence and their statistical entropy is measured. The entropy of the series is compared with that of shuffled copies. Random data and pink noise have the same recurrence entropy as their shuffled copies. Periodic series have high recurrence entropy when the embedding corresponds with the period; recurrence entropy and arrangement vary inversely in periodic data. Empirical series, chaotic, biotic and many stochastic series have significant recurrence entropy at multiple embeddings, but much lower in creative processes than in periodic series. These and other results indicate that recurrence entropy is a measure of order, not of complexity (see Parts 8 and 9).

Considering together the statistical entropy and the recurrence entropy of time series (figure 6) allows one to distinguish different types of processes. Random series, which have high statistical entropy, have near zero recurrence entropy; this indicates diversity without order. Periodic series have high recurrence entropy, while their statistical entropy depends on their periodicity, ranging from 1 for period 2 to near maximal for sine waves. Heartbeat series, galaxy series, mathematical bios and stochastic noise have high statistical entropy and much higher recurrence entropy than their shuffled copies.

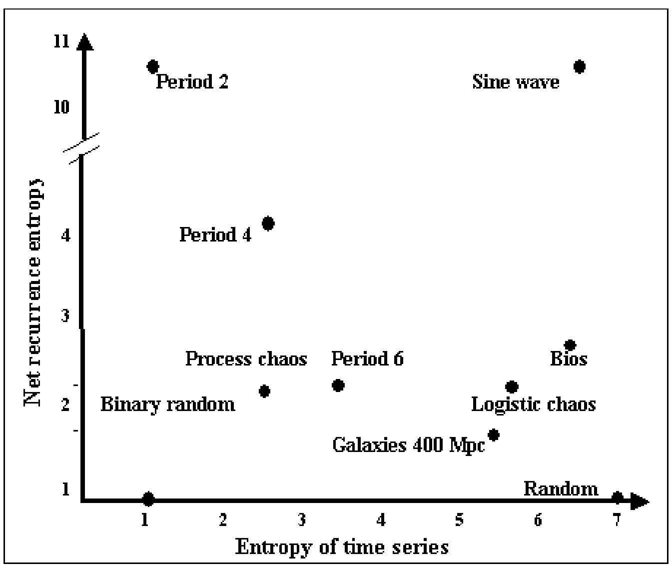

Figure 6: Cartesian plot of one-dimensional statistical entropy and multidimensional recurrence entropy distinguishes simple and complex processes. X-axis: Statistical entropy (100 bins). Y-axis: Recurrence entropy (50 embeddings) of the time series minus the recurrence entropy of shuffled copies.

4.6 Clinical relevance: illness and aging decrease entropy

The statistical entropy of heartbeat series is lower in older persons. It is also decreased in patients with coronary artery disease (CAD) (figure 7). Entropy is particularly reduced after myocardial infarction as reported by the Soviet cardiologists Khalfen and Temkin [see Zbilut (1991)], and during episodes of angina [Carlson-Sabelli et al (1995)]. Whereas entropy in control subjects never was lower than 1.0, periods of lower entropy (from 0.2 to 0.9) were observed in CAD subjects particularly during the early morning. These results are consistent with published reports indicating that the entropy of heartbeats is lower with aging, lack of physical training, male sex, and other factors that predispose to cardiovascular illness [Ryan et al (1994)]. Since vitality implies activity and change, aging and illness may be expected to decrease entropy production. Since illness and aging are exemplary forms of decay, these results demonstrate that the entropy of a time series does *not* measure decay.

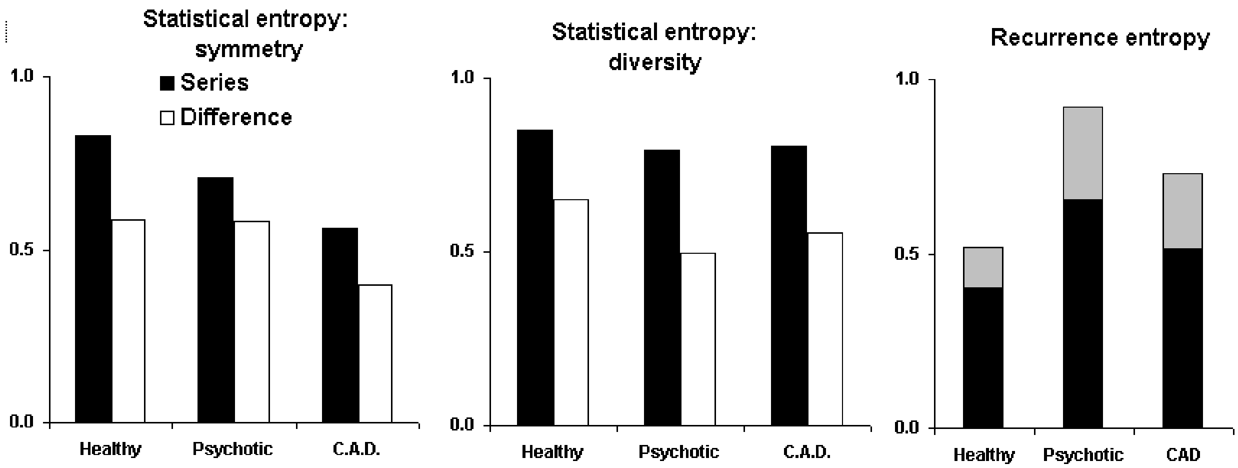

Figure 7: Statistical and recurrence entropy in healthy subjects, psychotics and coronary artery disease (CAD) patients. Average $\pm$ S.D.

The recurrence entropy of heartbeat series is higher in cardiac than in healthy persons; similar results have been obtained in another group of patients [Carlson-Sabelli et al (1995)]. Also heartbeat series of psychotic patients show higher recurrence entropy (figure 7). Recalling that recurrence entropy is higher in periodically ordered series than in creative processes, which in turn show higher recurrence entropy than random data, these results are at variance with the description of illness as “disorder”.

4.7 Entropy of mathematical chaos and bios

Time series generated by mathematical recursion provide a way to study the relation between entropy and pattern. In the series generated by the logistic equation, entropy increases monotonically: it is lowest for steady state (equilibrium), larger for periodic series, and still larger for chaos. In the series generated by the process equation, entropy transiently decreases in the transition from chaos to bios (figure 8), and then increases again, and it is maximal for infinitation. Thus, the entropy of this series first increases with complexity, then *decreases* with the expansion of chaos into bios, and finally increases with the simple order of infinitation. The biotic decrease in entropy is readily understandable, as bios is more asymmetric than chaos (Part 4). The maximization of entropy during infinitation shows again that entropy does not increase with disorder.

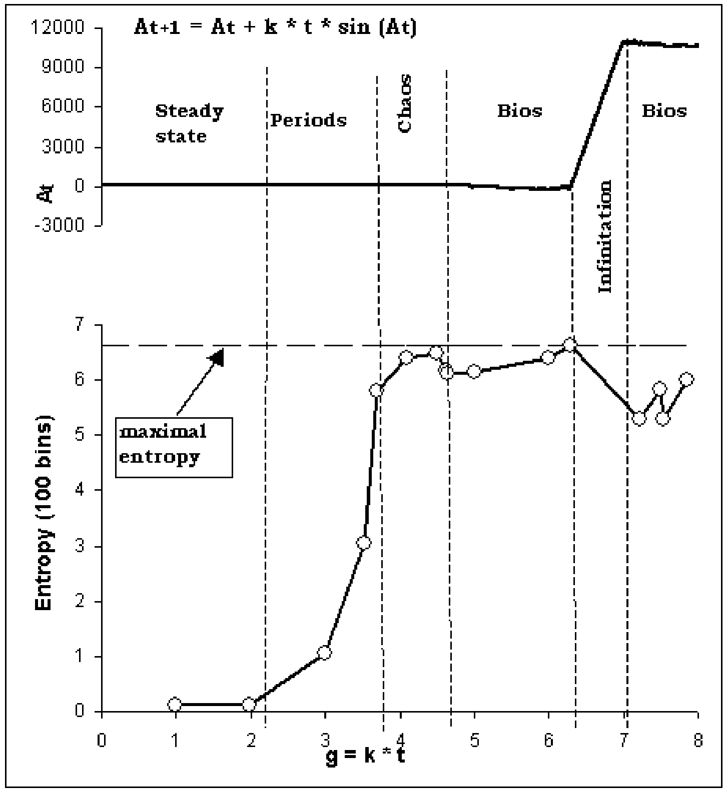

Figure 8: Variations in statistical entropy with pattern in the process equation. Top: time series generated by this recursion. The scale necessary to present bios and infinitation prevents distinction of the periodic and chaotic phases. Bottom: Statistical entropy attains its possible maximum during infinitation. Note that the entropy of bios is lower than that of chaos.

5. Empirical interpretation of statistical entropy

The objective of bios data analysis is to provide analytic techniques for the study of empirical processes, but the results obtained with these methods also offer some insights into the nature of entropy:

- **Entropy increases with diversity and symmetry.**
- **Entropy does not measure disorder or decay.**
- **Maximal entropy is associated with order.**
- **Entropy decreases with the generation of bios.**
- **Entropy rises and falls (nonperiodic cycling rather than monotonic decay).**

Entropy increases with diversity and symmetry. Process entropy is, as far as we know, the only method that demonstrates that entropy measures both symmetry and diversity, and allows one to analyze these two components separately. The identification of entropy with symmetry and diversity (rather than disorder) may also apply to nature. What is true for statistical entropy must also be true for the statistical mechanical formulation of thermodynamic entropy. That statistical entropy increases with diversity and symmetry suggests that evolution may be fueled and directed by a flow from asymmetry to symmetry and from sameness to diversity. Expansion increases both symmetry and diversity. Only within a closed chamber does the expansion of gas leads to macroscopic rest, in which multiple microscopic states are undistinguishable from one other. This macroscopic rest is due to the resistance of the walls, not to a hypothetical equilibrium. As soon as we open the chamber, the gas spontaneously expands, increasing entropy, diversity, and symmetry.

Entropy does not measure disorder or decay. The term order is used ambiguously, e.g. to mean regular arrangement, nonrandom organization, symmetry or asymmetry. In mathematics, order is defined as sequence by the order relation $\leq$ of lattice theory [Birkhoff (1931)]. Thereby mathematics models nature, where temporal sequence is the most fundamental form of order. Every other order is generated within time; N-dimensional order can be represented by N series. Statistical entropy is *not* a measure of disorder because perfect order has maximal entropy; moreover, shuffling data does not change its entropy. Recurrence entropy is associated with order. Statistical entropy is not a measure of complexity because it is lower in complex biological processes than in simple linear growth. Also, it does not change linearly with obvious changes in complexity such as the addition of sine waves. Decay may be defined mathematically as a reduction in complexity and empirically as aging, illness, and death. Measuring the entropy of heartbeat series in which decay can be unambiguously defined by aging and illness shows that statistical entropy does not increase with decay, and that recurrence entropy increases with illness and aging.

The origin and evolution of the universe, the synthesis of new elements in stars, and the emergence and evolution of life, among many other processes demonstrate that evolution occurs spontaneously. The interpretation of entropy as disorder and decay is a philosophical overlay that does *not* derive from its mathematical definition and it is unsupported by empirical observations. The interpretation of entropy should be determined by the empirical results obtained with known data. Measurements quantify what they actually measure, not what they are expected to measure. Saying that entropy measures disorder, decay, uncertainty or complexity, does not make it so. This use of the term "entropy" is determined by history, custom, and authority, but in science, the only valid definitions are those that emerge from operational analysis.

Maximal entropy is associated with perfect order. As entropy is a measure of uniformity, it is not surprising that maximal statistical entropy is attained for sequences of equally spaced terms that monotonically grow toward infinity. Correspondingly, in three dimensions, maximal entropy would obtain for an expanding sphere, as embodied in expanding gases and the expanding universe. In contrast, the interpretation of the maximization of entropy as a spontaneous involution towards disorder and rest contradicts the empirical evidence for cosmological, biological, and human evolution.

Entropy decreases with the generation of bios. In mathematical recursions, entropy increases in the average from steady state equilibrium to periodicity to chaos to bios to infinitation, but a transient decrease occurs in the transition from chaos to bios. The biotic reduction in entropy may contribute to the reduction in entropy proposed to account for biological organization as postulated by Schrödinger and Prigogine.

Entropy rises and falls, suggesting nonperiodic cycling. Entropy rises and falls not only in biological and non-biological systems in the planet but also in the distribution of galaxies as a function of time, at variance with the unidirectional maximization proposed by Clausius. An alternative to consider is a return to Carnot's view of an asymmetric but bi-directional exchange of energy between organized processes (work) and disorganized flux (heat) [Sabelli (1989)]. In open systems, heat and waste do not built up as randomness in a closed system, nor they simply diffuse away to an external sink.

6. Conclusions

We are obviously far from accounting for evolution in thermodynamic terms, but it may perhaps be advisable not to remain bound to explanations applicable to simple processes. Shannon's theory of communication focuses on the transmission of information by wires. To state that Shannon's theorems prohibit the generation of information by processes such as biological organisms is an unwarranted overgeneralization. Obviously, a system can increase total information when receiving multiple signals and combining them with previously held information. In a similar manner, Boltzmann created a brilliant and successful model to account in mechanical terms for thermodynamic changes in simple physical processes such as gas expansion, but its generalization to the universe at large requires firmer foundations. Simple models of entropy maximization do not account for well-known physical processes ranging from the movement of electrons in atoms to the expansion of the universe; it seems unlikely that it will account for biological processes. It seems, however, that the maximization of entropy must be in some way related to evolution [Lotka (1945); Black (1978); Brooks and Wiley (1984); Collier (1986)]. Symmetry and diversity are the two factors that foster the generation of complexity in catastrophes and in bipolar feedback processes (see Part 3), one may be tempted to speculate that the maximization of entropy may foster complexity. In this case, the generation of life and mind would be very probable processes, not improbable events.

Acknowledgements: This research was supported by the Society for the Advancement of Clinical Philosophy, and gifts from Mrs. Maria McCormick. We are thankful to A. Abouzeid, L. Carlson-Sabelli, K. Keelan, J. Konecki, and Donald H. McNeil for useful discussions.

References

Black, S. (1978). On the Thermodynamics of Evolution. *Pers. Biol. Med.* 21: 348-346.

Birkhoff, G. (1931). *Lattice Theory*. Providence, RI: Amer. Math. Soc. Colloquium Publ.

Brooks, D. R. and Wiley, E. O. (1986). *Evolution as Entropy.* Chicago: University of Chicago Press.

Bunge, M. (1986). Review of C. Truesdell Rational Thermodynamics. *Philosophy of Science* 53:305-3-6.

Carlson-Sabelli L., Sabelli HC, Patel, M, Messer, J, Zbilut, J., Sugerman, A., Walthall K., Tom, C. and Zdanovics, O. (1995) Electropsychocardiography. Illustrating the Application of Process Methods and Chaos Theory to the Comprehensive Evaluation of Coronary Patients. Complexity and Chaos in Nursing 2: 16-24.

Carlson-Sabelli, L., Sabelli, H., Messer, J., Patel, M., Sugerman, A., Luecht, R., Walthall, K.. (1996). Cardiac Entropy is Decreased in Coronary Artery Disease: Clinical and Physical Significance. *Proceedings of the International Systems Society, 40th meeting*. M. L. W. Hall (Ed.). Louisville, Kentucky. Sustainable Peace in the World System, and the Next Evolution of Human Consciousness. pp 165-176.

Chaisson, E. (1987). *The Life Era*. Atlantic Monthly Press.

Cohen, J. and Steward, I. (1994). *The Collapse of Chaos*. New York: Penguin.

Colless, M. M. (1999). First Results from the 2dF Galaxy Redshift Survey. *Phil. Trans. Roy. Soc. Lond.* Available: http://arxiv.org/abs/astro-ph/9804079

Corning, P.A. and Kline, S. (1998). Thermodynamics, Information and Life Revisited, Part I: 'To Be or Entropy'. *Systems Research and Behavioral Science* 15: 273-295.

Clynes, M. (1969). Cybernetic Implications of Rein Control in Perceptual and Conceptual Organization. Annals New York Academy of Sciences 156: 629-670.

Ebeling, W., Molgedey, L., Kurths, J., and Schwarz, U. (2002). Entropy, Complexity, Predictability, and Data Analysis of Time Series and Letter Sequences. In *The Science of Disasters,* A. Bunde, J. Kropp, and H.J. Schellnhuber (Eds.). Berlin: Springer.

Engels, F. (reprinted 1940). *Dialectics of Nature.* New York: International Publishers.

Gal-Or, B. (1972). Entropy, Fallacy, and the Origin of Irreversibility: An Essay on the New Astrophysical Revolutionary School of Thermodynamics. *Annals of the New York Academy of Science* 196: 307-325.

Georgescu-Roegen, N. (1971). *The Entropy Law and the Economic Process*. Cambridge, Mass.: Harvard University Press.
Gell-Mann, M. (1994). *The Quark and the Jaguar.* New York: W. H. Freeman.
Haldane, J. B. S. (1960). Pasteur and Cosmic Asymmetry. *Nature* 185: 87.
Layzer, D. (1967). In *Relativity Theory and Astrophysics,* J. Ehlers (Ed.). Providence, RI: American Mathematical Society, p 237.
Lotka, A.J. (1922). Contribution to the Energetics of Evolution. *Proceedings of the National Academy of Sciences* 8: 147-155.
Prigogine, I. (1980). *From Being to Becoming. Time and Complexity in the Physical Sciences*. San Francisco: W. H. Freeman.
Prigogine, I. (1997). *The End of Certainty*. New York: The Free Press.
Ryan, S. M., Goldberger, A. L., Pincus , S. M., Mietus, J and Lipsitz, L.A. (1994). Gender- and Age-related Differences in Heart Rate Dynamics: Are Women More Complex than Men? *Journal of American College Cardiology* 24: 1700-1707.
Sabelli, H. (1989). *Union of Opposites: A Comprehensive Theory of Natural and Human Processes.* Lawrenceville, VA: Brunswick Publishing.
Sabelli, H. (1994). Entropy as Symmetry: Theory and Empirical Support*. Proceedings of the International Systems Society 38th Annual Meeting,* B. Brady and L. Peeno (Eds.). Pacific Grove, CA, pp. 1483-1496.
Sabelli, H. and Carlson-Sabelli, L. (1999). Process Methods and the Identification of Biotic Patterns of Heartbeat Variation. *Proceedings of the 4th Systems Science European Congress,* L. Ferrer et al (Eds.). Valencia, Spain, pp 493-502.
Sabelli, H.C., Carlson-Sabelli, L., Javaid, J. I. (1990). The Thermodynamics of Bipolarity: A Bifurcation Model of Bipolar Illness and Bipolar Character and Its Psychotherapeutic Applications. *Psychiatry: Interpersonal and Biological Processes.* 53:346-367.
Sabelli, H.C., Carlson-Sabelli, L., Zbilut, J., Patel, M., Messer, J., Walthall, K. and Tom, C. (1994). Cardiac Entropy in Coronary and Schizophrenic Patients, and the Process Concept of Entropy as Symmetry. *Cybernetics and Systems`94.* 2: 967-974, R. Trappl (Ed.). Singapore: World Scientific Publishing Company.
Sabelli, H., Patel, M., Carlson-Sabelli, L., Sugerman, A., and Messer, J. (1995). Entropy as Diversity and Organization in Living Systems. *Proceedings of the International Society Systems Sciences* 113-124.
Schrödinger, I. (1945)*. What is Life?* Cambridge: Cambridge University Press.
Thorne, K. S. (1994). Black Holes & Time Warps: Einstein's Outrageous Legacy. New York: W.W. Norton & Company.
Wicken, J. S. (1987). *Evolution, Thermodynamics and Information*. New York: Oxford Univ. Press.
Wicken, J. S. (1989). Evolution and Thermodynamics: The New Paradigm. *Systems Research* 6: 181-186.
Wolfram, S. (1983). Statistical Mechanics in Cellular Automata. *Reviews of Modern Physics*. 55: 601-642.
Yates, F. E. (1987). General Introduction. *Self-Organizing Systems. The Emergence of Order.* F. E. Yates (Ed). New York: Plenum Press.