Mini Review

Complexity Control (CC) within Living Networks

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Abstract

Herein we point out the importance of crucial events in living networks and clarify the difference between the empirical perturbative method of Complexity Matching and Management Effect (CMME) and the the recent extension of these concepts to the interactive method of Complexity Control (CC). Ashby's Law explaining the need for higher complexity in driving one complex network by another is argued to be equivalent to CC. Consequently, the CC is identified rather than CMME as the appropriate mechanism for explaining the information flow is consistent with Ashby's Law. A major conclusion reached is that because Ashby's Law is equivalent to CC the theoretical basis used to explain a number of empirical results are wrong.

Introduction

Scientists who during the Second World War had devoted their talents to the making (encryption) and breaking (decryption) of codes, enhancing signal- to-noise ratios in various sensors so as to increase the lethality of weapons, and other such activities, turned their scientific skills and attention to the metaphoric beating of their intellectual swords into ploughshares. W. Ross Ashby was an early convert to the importance of complexity, through the use of Cybernetics [1], in quantifying natural phenomena and formulated a law on how to control and regulate complex networks leading to what he called "The Law of Requisite Variety" [2] but herein we use the name "Ashby's Law" [3]:

Any system that governs another, larger complex system must have a degree of complexity comparable to the system it is governing. Unfortunately, Ashby's Law in its present form failed to capture the imagination of the broader scientific community. The recognition of its significance was not fully appreciated until after it was rediscovered over a half century later by West et al. [4] while studying the exchange of information among various forms of dynamic complex networks, resulting in the Complexity Matching and Management Effect (CMME). In the latter situation, a complex network can be anything from an organization to an organism, including one of the most complex of organ-networks (ONs) known to man, that of the human brain.

A working measure of a network's complexity is determined by the degree of roughness of the ON's time series X(t) which is determined by the inverse power law (IPL) index of the probability density function (PDF). This IPL index is a consequence of the scaling behavior of the time series $X(\lambda t) = \lambda^{\delta(t)} X(t)$ which is a mono factual dimension when the scaling parameter $\delta(t)$ is a constant and is a multifractal dimension when it is time dependent. The scaling 'equality' is interpreted in terms of the scaled PDF in phase space: $P(x,t)=t^{-\delta(t)}\ F\ xt^{-\delta\ (t)}$, where the unknown function F(.) is the solution to a Fractal Kinetic Equation (FKE) first derived and solved by Zaslavsky et al. [5].

The complexity can therefore be expressed in terms of statistical properties of crucial events (CEs), which are a subset of renewal events (REs) introduced into statistical analysis by Feller [6] and have identically distributed independent (IDI) random events. A CE time series (CETS) was subsequently identified as those REs that have IPL PDFs generated by a process of spontaneous self–organized temporal criticality (SOTC) [7,8]. The complexity of CETS is defined by the waiting-times τ of the intervals between consecutive CEs which have an IPL PDF $\tau^{-\mu}$ with the IPL index μ in the interval $1< \mu <3$. This heavy-tailed complexity has been shown to manifest it self in the empirical distributions of: wealth [9], the size of cities[10], of word usage [11], of heartbeats [12], and of brain signals [13] to name a few of the over 50 empirical heavy-tailed PDFs listed in [14] covering disciplines as different as Anthropology is from Zoology.

Mahmoodi et al. [15,16]and West et al. [17] have shown that the multifractal dimension MFD D(t) is equal to the IPL scaling index $D(t)=\mu(t)$ and is consequently related to the scaling index by means of $\mu(t)=2-\delta(t)$, thereby enabling the direct transfer of information between ONs to be achieved using computational models.

Consequently, during an information exchange between two ONs, the ON with the greater instantaneous MFD (D>(t)) will transmit the information and the ON with the lesser instantaneous MFD (D<(t)) will receive the information independently of all other considerations, which is equivalent to Ashby's Law in the present context.

This information transfer was recently shown by Mahmoodi et al. to be due to complexity control (CC) in living networks [3] thereby replacing CMME as we show below. Furthermore, it is also shown that it is the CC and not CMME that is equivalent to Ashby's Law.

CETS and Information Exchange Among ONs

The CE time series (CETS) is the most important concept in discriminating between CMME and CC in processing empirical time series. We have come to understand that CETS are foundational for the formation of any quantitative theory of medicine or its complimentary theory of rehabilitation [18], including the formulation of any theory of information transfer among ONs whether one or all are healthy, ill/injured or a combination of the two. Consequently, we list the results of studies leading to this new viewpoint. The temporal complexity intrinsic to CEs is used to distinguish CC from CMME [3].

Given the limiting format of a Mini Review the key points of a CETS are listed here given its definition as a discrete time series with statistically independent time intervals τ between consecutive events:

a) CEs are a subset of REs

b) CEs have IPL probability density functions (PDFs) for the time intervals between events

c) the waiting-time PDF is $\tau^{-\mu}$, where the IPL index is in the interval $1< \mu <3$ and the CETS are ergodic when $3> \mu >2$ and non- ergodic when $2>\mu >1$

d) the IPL index μ is taken to be the working measure of complexity of the CETS and, as such, is equal to the multifractal dimension (MFD) $\mu(t) = D(t)$

e) A second IPL for CETS appears in the Power Spectrum Density (PSD) in terms of the frequency $f: S(f) \propto f^{-\beta}$, where the IPL index in this case is $\beta = 3 - \mu$ and consequently falls in the range $0 < \beta < 2$

f) the PSD IPL index at the value $\beta = 1$ gives rise to 1/ƒ — noise at the border between ergodic and non-ergodic time series (μ=2) [13], whereas for other values of μ we refer to the CETS as having 1/ƒ —variability [18]

CC dynamic model

We introduced a dynamic model for complexity control (CC) between networks, represented by time series characterized by different values of their temporal complexity measures, as indicated by their respective IPL indices. Given the apparent straight forward character of the model and the generality of the result, we [3] formulated a hypothesis based on the closeness of the scaling measures of the model to the empirical complexity measures of the human brain.

The main differences between the empirical CMME model and the current CC model are itemized as

a) CC is based on reinforcement learning (RL), while CMME is an effect based on linear response theory [19]

b) CC depends on the form of the interaction [3], while CMME is independent of the strength of the perturbation [4]

c) the complexity of the interacting networks in CC changes over time, whereas in CMMEs the two complexities remain unchanged during the perturbation

d) CC is manifest within single ON time series, while CMMEs only appear at the level of large ensemble averages and in the asymptotic regime.

Complexity Control (CC) and Physiological Networks

A central aspect of a healthy physiological ON is that it must continually find a way to adapt to dynamic environmental uncertainty, and this adaptation strategy must succeed in a time-constrained, high stakes situation [20]. ONs – which include whole organisms, the organ networks that give rise to these organisms, and the innumerable inter-cellular and intra-cellular ONs nested within these organs – that accomplish this adaption strategy typically correspond to health; ONs that cannot achieve this adaptation strategy correspond to disease. The most dramatic example for the need to achieve successful ON adaptation in an extremely time-constrained and high stakes situation occurs on the day we are born. A fetus must rapidly transition from life in an intra-uterine home to the profoundly distinct extra-uterine physical environment they will live in as a newborn infant. While many neonates successfully achieve this adaptation on their own, many also unfortunately do not, which can manifest in life-threatening disease that require emergent clinical attention [21]. Another example is Multiple Organ Dysfunction Syndrome (MODS), where an acute environmental stressor actively interferes with inter-organ communication, eroding the capability to coordinate an adaptive response that can sustain health [22-24]. The second example is associated with organs functionally decoupling from the patient's physiological network, manifesting as clinical loss of function at the bedside; when four or more organs fail in this context, survivability unfortunately plummets to zero %.

There exists a profound unmet need in clinical medicine to translate the conceptual framework of health and adaptivity into a capability that can measure inter-organ communication at the patient's bedside in real-time. The paradigm of Complexity Control (CC) is a promising candidate that can address this unmet need [3]. For example, recent work involving the CC paradigm showed that it is possible to measure real-time dynamic communication between the heart, brain and lung purely from simultaneously measuring their associated bedside time series [17,25]. The conceptual engine of CC involves Reinforcement Learning (RL), which entails continual two-way cross talk between an agent and its changing environment, which is the central concept of adaptation [3].

Conclusion

Consequently, CC is a proper dynamic model for representing systems that can phenotypically change because of continual bidirectional cross talk across their respective spatiotemporal scales of function. This is explicitly codified by RL's mutual feedback mechanism between these interacting systems.

Aside from human disease and rehabilitation, a compelling frontier of CC application at a much larger functional and temporal scale is the theory of punctuated equilibria (PEQ) in paleontology [26]. Historically, PEQ emerged as a paradigm in response to the lack of empirical evidence in the fossil record for incremental gradual uniform evolution of organisms; rather, empirical evidence suggests that organisms evolved rather rapidly, in short bursts randomly spaced at independent IPL time intervals, and not incrementally. In the case of ON, CC can be used to understand phenotypical changes in the setting of the health, disease, and rehabilitation; in the setting of paleontology, CC can be used to understand phenotypical changes that correspond to speciation events.

CC is an appealing paradigm to understand emergent phenotypical changes as a consequence of the interaction of systems across a wide set of spatiotemporal scales in a variety of functional contexts: optimizing personal health via inter-ON communication for coordinating an effective adaptive response, locomotion

rehabilitation in a senior citizen in setting of arm-in-arm walking [27], or at the most extreme level, speciation due to interaction between organisms and the environment as in PEQ [26].

This identification of CC rather than CMME as the appropriate mechanism for explaining the information flow is consistent with Ashby's Law. A major conclusion reached is that because Ashby's Law is equivalent to CC the theoretical basis used to explain a number of empirical theories are inaccurate. Two important misinterpretations are the restoration of complexity of locomotion in senior citizens through arm-in-arm walking for one and *punctuated equilibria* for another.

The CMME interpretation of arm-in-arm walking [27] is apparently wrong because of the size in the initial misalignment of the complexities of the individuals doing the walking. The process of bringing the pathologically low level of complexity up to the level of normality cannot be achieved by any perturbative method such as CMME. Thus, any complexity matching method involving a perturbation is doomed to failure. On the other hand, the mismatch in complexities are easily relaxed by means of the information exchange in CC. A similar argument applies to the theory of PEQ [26] because of the large jumps taken at each step in the CE process [28].

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