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Editorial

Experimental complexity in physical, social and biological systems

There are a myriad of examples of dynamical systems displaying chaos and complex behavior, from the simple double pendulum, to the much more complex human brain or any social organization. They are typically characterized by the presence of nonlinear interactions governing their often unpredictable dynamical evolution, which makes it impossible to provide a simple description of their behavior even under controlled laboratory conditions. The very first (published) evidence of chaos in an experimental system was reported in 1977 by Jack Hudson and collaborators, who observed sustained time-dependent nonperiodic oscillations in the Belousov–Zhabotinsky reaction in a continuous-flow stirred reactor [1]. Before that, chaotic dynamics had been first noticed and recorded by Yoshisuke Ueda during his Ph.D. at the end of 1961 in an electronic realization of a driven Duffing oscillator —however, this work was only published in 1992 [2]. Other milestones of this early research into complex dynamical behavior include David Ruelle and Floris Takens' investigations into the mechanisms underlying turbulence. They introduced the term "strange attractor" and proposed theoretically that the transition to turbulence should be observed after just three or four bifurcations [3], and Gollub and Swinney showed experimentally that this mathematical result could be possibly observed in a rotating fluid [4]. A few years later, intermittences [5] and the routes to chaos [6] were found in a Rayleigh–Bénard experiment. After that, chaotic behavior was observed in many different fields of research, such as laser and nonlinear optics physics [7–9], plasma physics [10] and even in astrophysics [11]. Whether chaos is observed in biomedical data is still an open question, mostly because it is rather difficult to provide a conclusive proof for an underlying determinism [12]. Finally, while much of this experimental work concerns itself with temporal chaos, turbulence is complexity not only in time but also in space, and from its study the new field of spatio-temporal chaos and pattern formation in hydrodynamic systems emerged [13,14].

From these initial efforts, a whole new branch of science has emerged that encompasses not only physical, but also biological and social systems, featuring a healthy interplay between new experimental findings and theoretical analysis and modeling, and ranging from basic science to technological applications. The purpose of this Special Issue is to offer a collection of articles devoted to cover new advances in applications and experiments in different areas related to nonlinear dynamics and complexity. Specifically, the collection comprises eleven contributions reporting results on experiments or new methods for analyzing data in systems as diverse as a mechanical device with friction, a wind tunnel, observational data from the Gulf of Mexico, a culture neuronal network, electronic circuits, data from transportation systems and brain imaging (and other biomedical) datasets, highlighting the interdisciplinary and universal nature of the observed phenomena.

The issue opens with research articles devoted to the study of complexity in physical systems. In their contribution to this special issue, Maza and Schins [15] study the dynamics of a harmonically driven slider. This includes an experiment based on a friction-driven rimmed cylindrical slider, and a theoretical investigation that takes into account the stochastic nature of the dynamics. For small driver acceleration the slider is stuck to the substrate due to static friction, but above a given threshold, the dynamics becomes periodic, though not fully harmonic. The authors propose a Markovian model that considers the existence of two attractors, which is able to reproduce the experimentally observed quasi-triangular shape of the slider velocity signal, as well as the phase lag with respect to the driver. It shows that the dynamics must become harmonic for large enough driver accelerations.

Flows in the atmosphere, oceans or around urban environments are all governed by turbulence, the probably most complex phenomenon in nature. In this Special Issue, two contributions provide examples of spatial and temporal multiscale interactions in a complex, chaotic system such as the ocean [16] or turbulence in a wind tunnel [17]. In Ref. [16], Bracco et al. review recent results for which modeling has been fundamental to interpret observational data in the dispersion of oil and climate-relevant tracers in the Gulf of Mexico, ultimately evidencing the interplay of mesoscale and submesoscale circulations impacting the marine ecosystem and climate at all temporal scales.

Kalmár-Nagy and Varga analyze [17] two-component velocity measurements in a wind tunnel model. Their aim is to shed light on the temporal structure of turbulence around an urban environment, of which the wind tunnel is an idealized representation. To this end, velocity fluctuations are treated as a marked point process, and the data are transformed using the quadrant conditional sampling method. The information content of the symbol sequences that are a coarse-grained quadrant transformation of the velocity fluctuation time series is studied. A surrogate data analysis shows that the entropy distribution of the experimental data is qualitatively similar to that of a noisy periodic series, and that high-order Markov chains are necessary to capture the information content of the symbol sequence. If the quadrant method is performed with rotated coordinate systems, the entropy is close to minimal in the principal axes system of the velocity fluctuation

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cloud. These results will be useful for further explorations of the impulse transfer of turbulent flows.

In references [18] and [19], authors make use of the versatility of electronic circuits to implement dynamical systems with chaotic dynamics and study their synchronization properties. In [18], authors present a hybrid analog-digital system that describes a jerk circuit, using the Lur'e notation for a system of the type $\dot{X} = AX + B\psi$. The generalization of the jerk system is then presented and different cases that generalize the dynamics and behaviors are considered and studied. The main goal of this approach is to combine the best of each analog/digital part and simplify the analog circuit. The real advantage of using this hybrid circuits is that the digital part can be modified to easily change the dynamics of the jerk circuit, transforming the system into a nonlinear circuit (using multiplication terms) or into a 1-D double scroll or multi-scroll circuits.

Concerning the interaction between nonlinear electronic circuits, Castañeda et al. [19] analyze the real-time synchronization between a discrete-time recurrent neural network and the Genesio & Tesi chaotic oscillator. This is done by generating the dynamics of this chaotic system by means of an Arduino microcontroller, where two state space variables are captured in a compact development system. These variables are synchronized by an artificial neural network, where the Kalman filter is used for the training algorithm and where it is possible to achieve the synchronization between the neural convergence and the chaotic plant state. Interestingly, the procedure presented in this work constitutes a precedent towards the development of a portable and compact encryption prototype.

This special issue also includes several manuscripts dealing with the complexity exhibited by biological systems. The deep relationship between the structure and function in a complex network is evaluated from a new perspective by Tlaie et al. [20], where the statistical complexity of the time series of a single element of a dynamical complex network is found to be correlated with its topological role. The new method is applied to experimental data of cultured neuronal networks. After a detailed topological study of the experimental network structure, a neurodynamics model is simulated on top of the physical networks to show that nodes of higher connectivity display a lower complexity in their dynamical behavior. These results point out to a new way to infer the degree distribution of the network connectivity from individual dynamical measurements.

To ease the burden of simulating biological models which can sometimes require tens of variables, large domains or hundreds of parameters to describe their physiological dynamics, Fenton et al. [21] have developed an interactive and self-customised library within the WebGL framework to allow real-time simulations of a quite broad range of time-dependent complex nonlinear dynamics. For example, they show ventricular fibrillation in rabbit ventricles using a simple model of the electrical activity of a cardiac cell derived from sub-cellular, cellular, and tissue experimental data developed by Gray and Pathmanathan [22].

The next contribution is an example of how complexity science may lead to important practical applications in health science. Obstructive Sleep Apnea (OSA) is a potentially serious sleep breathing disorder whose evolution is difficult to predict. When it is not treated, OSA might lead to severe cardiovascular and metabolic complications. In the contribution made by Zanin et al. [23], the authors make use of the tools of complex networks to characterize the relationships within a group of patients through the recently proposed convergence/divergence formalism. They manage to detect relevant subcommunities and use this topological information to train models that might help to forecast the progression of the disease. The novel method presented in this work yields more precise results than standard data mining models, and casts light on a promising new perspective to describe a disorder that affects around 3–6 of adult population. Furthermore, it is one additional evidence to support the experimental applicability of the science of complexity in the biomedical context.

Capturing the interplay between dynamical systems is still an unsolved issue, due to the complexity of the interactions between real systems and, in many situations, the inability of fully resolving the dynamical state of the variables describing the evolution of a system. In Echegoyen et al. [24], authors propose a new metric to quantify the synchronization between two (or more) dynamical systems from the observation of one of their variables. From the time series of the dynamical systems, authors construct symbolic patterns capturing the order of the magnitude of the observed variable inside state vectors of length D. Next, they compute the alignment of these vectors to quantify the amount of synchronization between the two dynamical systems. In this way, the *ordinal synchronization* is able to measure both the phase relation between oscillators and a certain amplitude coordination given by the order within the ordinal vectors. Interestingly, authors show how this methodology can be applied to analyze brain imaging datasets, capturing the interplay between the sensors of magnetoencephalographic recordings during resting state of an individual, which could be used to the construction of the subsequent functional networks. Furthermore, experiments with electronic circuits representing the Lorenz model show that the methodology is robust for different amounts of coupling between oscillators.

Finally, this special issue ends with two significant works. Among the many issues that must be addressed in the study of real-world networks, one of the most important ones is the definition and correct use of null models. The main reason to work with null models is that they let distinguish the importance of each topological property separately and, consequently, allow comparing networks with heterogeneous features. The contribution "On the use of random graphs as null model of large connected networks" by Wandelt et al. [25] aims at quantifying the error introduced by the use of a wrong null model. They find, after analyzing a large set of synthetic graphs and real-world examples drawn from transportation systems and brain functional networks, that a wrong null model introduces a significant bias, especially for macro-scale topological metrics and for networks with low densities. Then, they propose and validate an efficient algorithm for generating connected random networks, which outperforms the nave solution based on generating random graphs until a connected one is found.

In [26] a novel approach for analyzing high-dimensional data by using sparse graphs (neighborhood-similarity graphs) is introduced. This new method allows a transparent interpretation of data, without altering the original data dimension and metric, so distortions on data structure due to any dimensionality reduction are avoided. Authors present several applications to either synthetic and real dataset, including some standard image datasets that contain labeled images of single objects and 60,000 images of handwritten digits. The results obtained suggest a substantial role for neighborhood-similarity graphs in the future of data science that underlines idea of using complex network approaches for data analysis as a deep complementary technique.

In summary, new quantitative measures of experimental results, contaminated by noise and data resolution limitation, have been reported in this special issue, broadening the current state of the art in the field of experimental complexity as, surely, they will be useful to distinguish different types of complexity or patterns and to provide guidance to construct new models of the system's behavior.

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