A fundamental problem crisscrossing the fields of physiology and artificial intelligence is understanding how complex activity and behavior emerge from the intrinsic underlying structure and dynamics. To address this problem, we need new methodologies and tools to perform a comprehensive analysis of complex systems dynamics. Multifractal formalism and methodology enable us to investigate local interactions underlying physiological systems and quantify the organization of physiological temporal fluctuations and their cascades across scales (Plamen Ch. Ivanov et al., 1999, 2001; Ivanov et al., 2002; Mukli et al., 2015). Besides, we need a general network framework to examine networks of interactions among diverse subsystems across space and time scales that lead to emergent complex behaviors at the systems level (Bashan et al., 2012; P. C. H. Ivanov et al., 2016; Ivanov and Bartsch, 2014). Despite recent progress in the theory of dynamic networks, there are fundamental methodological and conceptual challenges in understanding how global states and functions emerge in networks of diverse dynamical systems with time-varying interactions and the basic principles of their hierarchical integration. In particular, when mining the time-varying complex networks structure and dynamics, one has to overcome various internal or external perturbations that can transiently or permanently mask the activity of particular nodes and their causal interactions (Gupta et al., 2019; Gupta et al., 2018; Xue and Bogdan, 2017a; Xue and Bogdan, 2019; Xue and Bogdan, 2017b).

Novel artificial intelligence techniques and machine learning algorithms may equip us with the tools to classify and predict the emergent behavior in dynamical networks based simultaneously on network topology and temporal patterns in network dynamics. Key insights and knowledge that emerge from multifractal and differential geometry concepts can help analyze and quantify their complexity. Furthermore, they allow us to determine the most efficient network architecture to generate a given function, quantify key universalities, and identify new theoretical directions for
artificial intelligence and machine learning based on physiological principles (Richards et al., 2019). Ultimately, we will attain sustainable systems that enjoy seamlessly indistinguishable features of physiological systems (Wu et al., 2021).

From genomic, proteomic, and metabolic networks to microbial communities, neural systems, and human network physiology of organ systems, complex systems display multi-scale spatiotemporal patterns that are frequently classified as non-linear, non-Gaussian, scale-invariant, and multifractal (Bassingthwaighte et al., 2013; Ivanov et al., 2009; Stanley et al., 1999; West and Zwielf, 1992). While several efforts have demonstrated that electromyographic signals possess fractal properties (Sanders et al., 1996; Xue et al., 2016; Garcia-Retortillo et al., 2020; Rizzo et al., 2020), (Martin del Campo Vera and Jonckheere) report a complex bursting rate variability phenomenon where the surface electromyographic (sEMG) bursts are synchronous with wavelet packets in the D8 sub-band of the Daubechies 3 (db3) wavelet decomposition of the raw signal. Their db3 wavelet decomposition analysis reconstructs the sEMG bursts with two high coefficients at level 8, indicating a high incidence of two consecutive neuronal discharges. In contrast to heart rate variability (P. Ch Ivanov et al., 1998), the newly reported bursting rate variability phenomenon involves a time-localization of the burst with a statistical waveform matching between the “D8 doublet” and the burst in the raw sEMG signal. While this analysis focused on an available small cohort of patients, further comprehensive studies can elucidate the interdependencies between the electromyographic signals and other brain and physiological processes, determine the mechanism role, and implications for medical applications.

Quests for understanding the inner workings of complex biological dynamics have provided not only more appropriate and efficacious medical therapies but have also led to new artificial intelligence algorithms and architectures. For instance, inspired by early modeling of how biological neurons process information, the reservoir computer model—a type of recurrent neural network where the set of outputs are process information, the reservoir computer model and artificial intelligence have provided not only more appropriate and efficacious medical therapies but have also led to new artificial intelligence algorithms and architectures. For instance, inspired by early modeling of how biological neurons process information, the reservoir computer model—a type of recurrent neural network where the set of outputs are process information, the reservoir computer model—artificial intelligence and machine learning can be used to develop models that can understand and predict complex systems. These systems can be applied in various fields such as medicine, finance, and social science to solve problems that are too complex for classical algorithms to handle.

The works presented in this Research Topic collection and current advances in the field of fractal and multifractal investigations of physiological systems structure and dynamics, and their applications to artificial intelligence, outline new challenges and opportunities in multidisciplinary research and applications. Dealing with the heterogeneity, multi-modality, and complexity of physiological and artificial intelligence and machine learning algorithms requires rigorous mathematical and algorithmic techniques to extract causal interdependencies between systems across different scales while overcoming various noise sources. As such, progress in this direction will require new algorithmic strategies to quantify time-varying information flow among diverse physiological and artificial processes across scales and determine how it influences the system dynamics.

Furthermore, there is an urgent need to adopt a cross-scale perspective and a corresponding theoretical framework to investigate the multi-scale regulatory mechanisms underlying the overall network and its relation to emergent states and functions in physiological and artificial systems. This urges the interactions of statistical physics, non-linear dynamics, information theory, probability and stochastic processes, artificial intelligence, machine learning, control theory and optimization, basic physiology, and medicine, such that new theoretical and algorithmic foundations will emerge for analyzing and designing physiological and artificial systems.
Only then, the biomedical and engineering communities will be able to develop new control methodologies that do not seek to only enforce a specific reference value but rather ensure that the complexity and multifractality are restored to a desirable profile.

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