DY 42: Focus Session: Computing with Dynamical Systems: New Perspectives on Reservoirs and Applications I – Fundamentals

Reservoir Computing uses the dynamic response of driven dynamical systems to predict and analyze temporal signals. The best-known example is the Echo State Networks proposed by H. Jaeger in 2001, where the reservoir consists of a recurrent neural network. However, in recent years, other realizations have been proposed, in particular those in which the reservoir system can be implemented in hardware in a fast and energy-efficient manner (e.g., using optical components). Other recent developments concern the specific incorporation of prior (physical) knowledge about the source of the input signal (physics aware/informed Reservoir Computing) as well as various application examples in different disciplines. Therefore, the goal of this focus session is to highlight the rapidly advancing current developments in the field of Reservoir Computing in order to enable a direct scientific exchange between new methodological approaches and innovative applications.

Organized by Ulrich Parlitz (Göttingen), Kathy Lüdge (Ilmenau), and Christoph Räth (München)

Time: Thursday 9:30–12:15 Location: BH-N 243

Invited Talk DY 42.1 Thu 9:30 BH-N 243

Is predicting chaos and extreme dynamics possible? An overview of (some) scientific machine learning approaches — •Luca Magri — Imperial College London, London, United Kingdom

The ability of modelling reality to predict the evolution of complex systems is enabled by principles and empirical approaches. Physical principles, for example conservation laws, are extrapolative (until the assumptions upon which they hinge break down): they provide predictions on phenomena that have not been observed. Human beings are excellent at extrapolating knowledge because we are excellent at finding physical principles. On the other hand, empirical modelling provides correlation functions within data, which are useful when principles are difficult to deduce. Artificial intelligence and machine learning are excellent at empirical modelling. In this talk, the complementary capabilities of both approaches will be merged (scientific machine learning). The approaches will achieve real-time modelling and optimization of nonlinear, unsteady and uncertain dynamical systems with chaotic and turbulent dynamics, which exhibit extreme events. The focus of the talk is on computational methodologies for modelling and optimization of chaotic flows with data-driven strategies that involve reservoir computing. I will conclude the talk with some lessons that we have learnt, and a discussion on future directions including quantum reservoir computing.

DY 42.2 Thu 10:00 BH-N 243

Harnessing multistability: Expanding the capabilities of reservoir computers via multifunctionality — •Andrew Flynn[1], Vassilios Tsachouridis[2], and Andreas Amann[1] — [1]School of Mathematical Sciences, University College Cork, Cork, IrelandIreland — [2]Collins Aerospace Applied Research & Technology, Cork, Ireland

Multifunctionality describes a neural network's ability to harness multistability in order to perform various tasks without altering its network properties. In this talk we demonstrate the advantages of extending multifunctionality to the domain of artificial neural networks (ANNs). Multifunctionality unlocks several new machine learning application for ANNs such as: data-driven modelling of multistability, generating chaotic itinerancy, novel memory recall techniques, and reconstructing transitions present in the epileptic brain. We outline how multifunctionality has so far been realised in an artificial setting with a reservoir computer (RC), a dynamical system in the form of an ANN. We employ generalised synchronisation to describe how to train a RC to achieve multifunctionality and also explore some of the challenges involved in realising multifunctionality. Our results not only illuminate the exotic dynamics and exciting applications of multifunctional RCs but also highlight the importance of a dynamics-driven approach when training ANNs to display a broader level of intelligence by performing multiple tasks without compromising on explainability.

DY 42.3 Thu 10:15 BH-N 243

Generation of persistent memory using stable chaos in random neural networks — •Hiromichi Suetani — Faculty of Science and Technology, Oita University, Oita, Japan — International Research Center for Neurointelligence, The University of Tokyo, Tokyo, Japan

In high-dimensional nonlinear dynamical systems, it is well established that even when fixed points or (quasi) periodic orbits serve as stable attractors, the system often undergoes prolonged irregular transient states before settling into the attractor. This phenomenon is known as super transient chaos. Particularly within coupled dynamical systems comprising elements characterized by strong nonlinearities such as discontinuous changes, they may display unstable transient states concerning finite perturbations, despite their linear stability to infinitely small perturbations. This phenomenon is termed stable chaos.

In this study, we explore a version of random neural networks. We begin by quantifying trajectory instability using the finite-size Lyapunov exponent (FSLE) and presenting the corresponding phase diagram. Our findings confirm the presence of stable chaos in the critical region between periodic attractors and super-transient chaos. Additionally, introducing external input shows that stable chaos achieves generalized synchronization at a lower amplitude than super-transient chaos. Employing the reservoir computing framework, we reveal the utility of stable chaos in information processing tasks such as the delayed classification of nonlinear signals.

DY 42.4 Thu 10:30 BH-N 243

Enhancing reservoir predictions of chaotic time series by incorporating delayed values of input and reservoir variables — •Luk Fleddermann[1,2] and Ulrich Parlitz[1,2] — [1]Max Planck Institute for Dynamics and Self-Organization, Göttingen, Germany — [2]Institute for the Dynamics of Complex Systems, University of Göttingen, Germany

Chaotic time series can be predicted using linear readouts of driven reservoir dynamics. In the applied case, typically only time series of incomplete measurements, i.e. partial observations of the dynamical state, are available. We compare the performance of reservoir computing for time series predictions with complete and partial system state knowledge. By combining delayed values of input and reservoir variables, we increase the mean time length of valid predictions for partial observations of the dynamical state.

15 min. break

DY 42.5 Thu 11:00 BH-N 243

Prediction of spatio-temporal chaos using parallel reservoir computing in combination with dimensionality reduction — Kai-Uwe Hollborn[1], Luk Fleddermann[1,2], •Gerrit Wellecke[1], and Ulrich Parlitz[1,2] — [1]Max Planck Institute for Dynamics and Self-Organization, Göttingen, Germany — [2]Institute for the Dynamics of Complex Systems, University of Göttingen, Germany

Reservoir computers can be used to predict time series of spatio-temporal chaotic systems. Using multiple reservoirs in parallel has shown improved performances for these predictions. Similarly, enhancements can be achieved by reducing the dimensionality of the input data. To utilise both options for better predictions, we combine parallel reservoirs with a dimensionality reduction of the input data by Fourier transformation or principal component analysis. The performance of this hybrid approach will be illustrated and evaluated for data generated by a one-dimensional Kuramoto-Sivashinsky equation and a two-dimensional Aliev-Panfilov model describing chaotic spiral wave dynamics.

DY 42.6 Thu 11:15 BH-N 243

High Dimensional Hybrid Reservoir Computing — •Tamon Nakano[1], Sebastian Baur[1], and Christoph Räth[1,2] — [1]Institutfür KI-Sicherheit, Deutsches Zentrum für Luft-und Raumfahrt, Sankt Augustin/Ulm, Germany — [2]Fakultät für Physik, Ludwig-Maximilians-Universität, Munich, Germany

Reservoir Computing (RC) is getting popularity as an alternative solution for complex dynamical systems, where physically derived models reach their limitation. RC is by default fully data-driven method and is expected to learn the underlying system in the dataset. However RC can't do so for a lack of data quantity, for example. The hybrid approach is now recognized as a powerful option for it. The idea is to combine a knowledge-based model as a support (e.g. an imperfect governing equation) to the fully data-driven method. This combination can be done at the input, output layer of RC or both of them (respectively called, input-, output-, full-hybrid). Some studies have been already done, for example, input- and full-hybrid by Pathak et al.(2018), output-hybrid by Doan et al.(2019). Duncan et al.(2023) compared the performance of the three approaches and showed the superiority of output-hybrid compared to the others. The prior studies above have developed the hybrid approach in lower dimensional problems (e.g. 3 dimension). In this work, we will extend the hybrid approach to higher dimensional systems. This will allow to treat highly nonlinear and time evolutionary systems with system knowledge, such as fluid dynamics simulations and time evolutionary phenomena captured in 2 dimensional images.

DY 42.7 Thu 11:30 BH-N 243

Exploiting the Brownian motion of quasi-particles for unconventional computing — •Alessandro Pignedoli, Björn Dörschel, and Karin Everschor-Sitte — Faculty of Physics and Center for Nanointegration Duisburg-Essen (CENIDE), University of Duisburg-Essen

The Brownian motion of quasi-particles offer a natural way of exploring the configuration space of a system. By mapping computational problems into this phenomenon, an ensemble of these particles can effectively solve them in an energy-efficient manner [1]. In this regard, magnetic skyrmions, which are topologically stable magnetic whirls that have been shown to behave like interacting Brownian particles, are promising candidates [2]. In this work, we show that the natural stochastic movement of such quasi-particles, in a given environment, provides a tool to solve different optimisation problems [3,4]. This type of computation could open up a new paradigm of low-power, in-materio implementation of swarm intelligence algorithms.

[1] C. H. Bennett, Int. J. Theor. Phys. 21, 905 (1982); [2] J. Zázvorka, et al. Nat. Nanotechnol. 14, 658 (2019); [3] German Patent Application DE 10 2023 131 171, K. Everschor-Sitte, A. Pignedoli, B. Dörschel (2023); [4] German Patent Application DE 10 2023 131 706, K. Everschor-Sitte, A. Pignedoli, B. Dörschel (2023).

DY 42.8 Thu 11:45 BH-N 243

Designing Active Matter Systems for Reservoir Computing — •Mario U. Gaimann and Miriam Klopotek — Stuttgart Center for Simulation Science (SimTech), Cluster of Excellence EXC 2075, University of Stuttgart, Germany

Reservoir computing with physical systems is a candidate for next-generation computing [1,2]. It is a powerful method to solve challenging tasks such as chaotic time-series prediction. However, tuning an arbitrary reservoir – which may be *physical* – for optimal properties like its dynamical regime remains an open question. To approach this problem we use a novel flavour of reservoir commuting based on simple active matter models [3]. We systematically study how the predictive performance of our driven active matter reservoir depends on a variety of physical hyper-parameters – the number of agents, the extent of driver-reservoir interaction, as well as different noise types and forces. For each set, we characterize the spatio-temporal, heterogeneous, yet also collective dynamics of the swarm. We aim to understand optimal conditions for learning and inspire new forms of physical, natural, and bio-inspired computing.

[1] Tanaka, G. *et al.* (2019), *Neural Networks* **115**, 100-123.
[2] Nakajima, K. and Fischer, I. (2021). *Reservoir Computing.* Springer Singapore.
[3] Lymburn, T. *et al.* (2021), *Chaos* **31(3)**, 033121.

DY 42.9 Thu 12:00 BH-N 243

Contextual Alignment for Robust Learning in Dynamical Systems — •Max Weinmann[1,2] and Miriam Klopotek[1] — [1]University of Stuttgart, Stuttgart Center for Simulation Science, SimTech Cluster of Excellence EXC 2075, Stuttgart, Germany — [2]University of Stuttgart, Interchange Forum for Reflecting on Intelligent Systems, IRIS3D, Stuttgart, Germany

Dynamical systems have exhibited remarkable computational prowess, particularly in prediction tasks like reservoir computing [1]. Achieving efficient computational offloading to the reservoir demands precise alignment of system dynamics with computational requisites. This entails parameter tuning and input transformation to facilitate a natural representation within the system. While the significance of dynamical diversity and system memory is evident, tailoring systems for specific tasks remains challenging [2]; context plays a key role. Our study investigates cellular automaton and other complex model systems. We explore probabilistic and deterministic perturbations to alter system dynamics, offering contextual cues that optimize task-specific information processing capabilities. Our focus extends to identifying fundamental properties enabling a predictable, adaptable alignment, akin to a learning process, fostering robust model creation.

[1] Maass, W., Natschläger, T., and Markram, H. (2002). Real-time computing without stable states: A new framework for neural computation based on perturbations. Neural computation, 14(11), 2531-2560.
[2] Stepney, S. (2012). Nonclassical Computation-A Dynamical Systems Perspective. Handbook of natural computing, 2.