Spring College in the Physics of Complex Systems | (SMR 4056)

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Spring College in the Physics of Complex Systems at the ICTP on 2025

Investigation of Explosive Synchronization in Adaptive Multiplex Networks

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Abstract

This investigation examines synchronization phase transitions in multiplex adaptive networks, where nodes interact through diverse communication pathways. Multiplex networks provide enhanced insights into the structure and dynamics of complex real-world systems. Previous research has demonstrated that degree-frequency correlations and adaptive coupling strength can lead to explosive (discontinuous) phase transitions, while single-layer and multilayer synchronous phase transitions may exhibit either continuity or discontinuity depending on network dynamics. In this research, we reveal that global synchronization produces a broader hysteresis loop compared to local synchronization, with additional layers further widening the loop. We also find that adapting the order parameter reduces network defects in small-world networks. In directed Erdős–Rényi random networks, explosive synchronization persists but results in a narrower hysteresis loop relative to undirected networks. These findings are analytically substantiated using a mean-field approximation for single-layer networks. Lastly, we show that the frustration parameter can modulate the synchronization phase transition from discontinuous to continuous, providing new avenues for controlling phase transitions in complex network systems.

Introduction

Dynamic phase transitions in complex networks, such as explosive synchronization, are critical for understanding phenomena like epileptic seizures. This study examines synchronization transitions in adaptive multiplex, direct, and Small-World networks, analyzing the effects of edge weight alignment, layer number, and frustration parameters on phase transition and hysteresis loop width.

P01

Model

The model extends the Kuramoto model to two-layer adaptive networks, where each layer's dynamics are defined with coupling strengths adapted locally and globally. Synchronization is calculated for both local and global levels. Simulations use the fourth-order Runge-Kutta method on Erdős-Rényi networks with $N = 100$ and average degree $\langle k \rangle = 12$.

Results

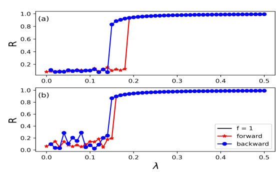

Figure 1: Comparison of explosive phase transition in single-layer random networks with global adaptive parameter (a) and local adaptive parameter (b). In this case, $f = 1$, $N = 100$, and $\langle k \rangle = 12$ are considered.

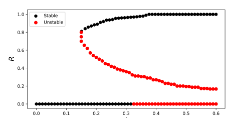

Figure 2: The numerical solution of R as a function of λ for Erdős–Rényi single-layer random networks with size $N = 100$ and $f = 1$ is shown. In this case, stable and unstable points are indicated in green and red, respectively.

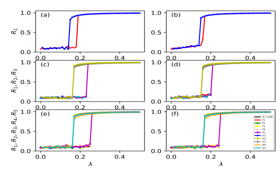

Figure 3: Synchronous phase transition for one-layer, three-layer, and five-layer networks considering the adaptive parameters of global (left column) and local (right column)

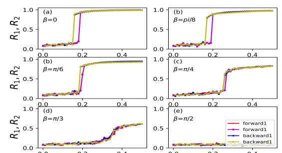

Figure 4: Synchronous phase transition changes from a discontinuous to a continuous state in a two-layer network with increasing frustration parameters. Here, the local adaptive parameter is considered.

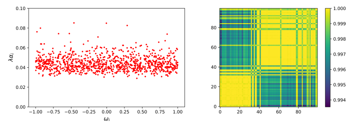

Figure 5: Correlation matrix for coupling coefficient$\lambda = 0.16$ (right) and frequency correlation diagram with adaptive coupling coefficient $(\lambda \alpha_i)$. Here, single-layer network and partial adaptive parameters are considered.

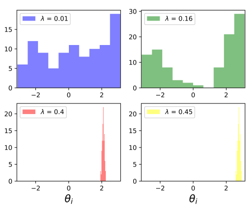

Figure 6: Density Phase transition functions with varying coupling strengths (λ) for a random two-layer network ($N = 100$, $\langle k \rangle = 12$, uniform frequencies in $[-1, 1]$). The first row shows the asynchronous state, and the second row the synchronous state.

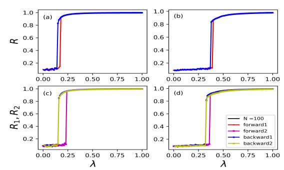

Figure 7: Phase transition in directed and undirected multilayer networks with global parameter adaptation ($\alpha_i = R$), for $N = 100$, average degree $\langle k \rangle = 12$, uniform frequency distribution in $[-1, 1]$, and $f = 1$. The left (right) column shows directed and undirected one-layer and two-layer networks.

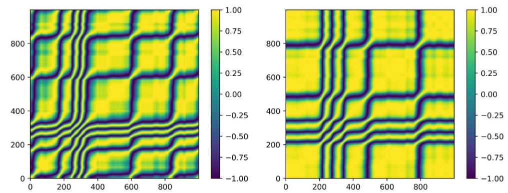

Figure 8: Comparison of the correlation matrix for a small-world network with non-adaptive (left) and adaptive (right) states ($N = 1000$, $p = 0.03$, $\lambda = 0.1$, $\langle k \rangle = 10$, $f = 1$), averaged over 20,000-time steps.

Conclusions

This study finds that explosive synchronization occurs in both single-layer and multiplex networks, with a stronger impact from global adaptive parameters. More layers widen the hysteresis loop, while the frustration parameter narrows it. The explosive phase transition is attributed to dynamic cluster formations rather than frequency-degree correlations, and adapting the order parameter reduces defects in small-world networks, enhancing synchronization dynamics.

References

[1] Bhim M Adhikari, Charles M Epstein, and Mukesh Dhamala. Localizing epileptic seizure onsets with granger causality. Physical Review E, 88(3):030701, 2013.

[2] Sergey V Buldyrev, Roni Parshani, Gerald Paul, H Eugene Stanley, and Shlomo Havlin. Catastrophic cascade of failures in interdependent networks. Nature, 464(7291):1025–1028, 2010.

[3] Sergio Gomez, Albert Diaz-Guilera, Jesus Gomez-Gardenes, Conrad J Perez-Vicente, Yamir Moreno, and Alex Arenas. Diffusion dynamics on multiplex networks. Physical review letters, 110(2):028701, 2013.

[4] Xiyun Zhang, Stefano Boccaletti, Shuguang Guan, and Zonghua Liu. Explosive synchronization in adaptive and multilayer networks. Physical review letters, 114(3):038701, 2015.

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P02

Poster

An intelligent complex system: Drones for monitoring in smart cities

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Multi-Unmanned Aerial Vehicle (UAV) systems exemplify a complex system characterized by numerous interacting agents [1], whose collective behavior can be utilized to address critical challenges in smart cities, including traffic management and public safety.

In this study [2], we examine the dynamics of swarm-based UAVs as an emergent system and propose a mathematical framework—the swarm-drone set covering problem—to optimize their deployment for large-scale traffic monitoring. The research specifically aims to minimize the number of UAVs required to surveil extensive road networks, achieving a balance between cost-efficiency and operational effectiveness.

Our computational experiments uncover a key emergent property of the system: increasing the coverage radius of individual UAVs reduces the overall number of UAVs required, illustrating how local interactions influence global outcomes. By situating multi-UAV systems within the framework of complex systems, this study underscores the importance of theoretical and computational tools in analyzing and optimizing the collective behavior of multi-agent systems.

[1] S. Agha et al., " Unmanned aerial vehicles (UAVs): practical aspects, applications, open challenges, security issues, and future trends", Intell. Serv. Robot., vol. 16, no. 1, pp. 109–137 (2023)
[2] F. A. Amarcha, A. Chehri, A. Jakimi, M. Bouya, R. Ahl Laamara and R. Saadane, "Drones Optimization for Public Transportation Safety: Enhancing Surveillance and Efficiency in Smart Cities," *2024 IEEE World Forum on Public Safety Technology (WFPST)*, USA, (2024)

P03

Fractional tumour-immune model with chemotherapy treatment

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Cancer is a group of diseases which cells grow uncontrollably and can spread into other tissues. Studies explore the complex interactions between cancer cells, host cells, and the immune system, while also considering various treatment approaches. To deepen understanding, mathematical models have been employed to analyze these interactions and the growth dynamics of cancerous cells [1]. We propose a fractional order model that describes some aspects of the interactions among host, effector immune, and cancer cells and chemotherapy treatment.. Due to the chemotherapy, sensitive cancer cells can suffer mutation and transform into resistant ones. We extend the tumour-immune model, splitting the equation of the cancerous cells into two equations: an equation for the sensitive cells and another for the resistant ones. We analyse a mathematical model governed by differential equations of fractional order to analyse the proliferation of cancerous cells [2]. Firstly, we analyse the model without chemotherapy. The normalised population of cells exhibits periodic behaviour after a transient time. In continuous drug delivery, the maximum values of cancerous cells depend on the chemotherapy dose and the mutation rate. We compute the maximum number of cancerous cells (sensitive cells + resistant cells) in a time interval. We verify that the size of the parameter space region in which the cancer is suppressed depends on the order value of the differential equation. The efficiency of the treatment changes according to chemotherapy and mutation rate. We show that not only the chemotherapy but also the drug resistance and the order value of the differential equation play an important role in the growth rate of cancer cells.

[1] C. Letellier, F. Denis, L.A. Aguirre, J. Theor. Biol. **322**, 7 (2013).

[2] A.P. Koltun, J. Trobia, A.M. Batista, E.K. Lenzi, M.S. Santos, F.S. Borges, K.C. Iarosz, I.L. Caldas, E.C. Gabrick, Braz. J. Phys. **54**, 41 (2024).

P04

Dynamics of spiral waves with variation of gel concentration in a chemical reaction-diffusion system

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Abstract

Spiral find its presence in various biological systems such as in cardiac tissue, neural tissues, in a growing colony of slime mould etc. In cardiac system, a normal electrical impulse might break due to the presence of some obstacle giving rise to spirals. These spiral causes irregular heart rhythm or arrhythmia. If this persists there is a potential of forming multiple spirals out of the existing ones, resulting in a total chaos which might be fatal. Thus it is necessary to study the dynamics of spiral waves. One of the best laboratory model for this is Belousov-Zhabotinsky (BZ) reaction-diffusion system. Researchers are trying to control the dynamics of spirals from last three decades in context of the cardiac wave dynamics. In this work we varied gel concentration to study its effect on the spiral rotation and we found gel concentration plays a role in governing wave properties of the spirals.

Keywords

Spiral waves; Excitable system; Cardiac arrhythmia; BZ reaction; Nonlinear dynamics

References

1. Nonlinearity in the Realm of Chemistry, S. Dutta, D. Mahanta, Physics News, 47, 52 (2017).

2. D. Mahanta, N. P. Das, and **S. Dutta**, Phys. Rev. E, 97, 022206 (2018).

3. Dynamics and Control of Spiral and Scroll Waves, **S. Dutta**, N. P. Das, D. Mahanta, in *Complexity and Synergetics*, edited by S. C. Muller, P. J. Plath, G. Radons, A. Fuchs (Springer Publishers, Heidelberg) 2018.

P05

Dynamic behavior of an active particle embedded in a smectic liquid crystal

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Self-propelled (active) swimmers exhibit fascinating dynamic behavior with relevance to a wide range of disparate systems found in biology, chemistry, and physics [1]. When embedded in a smectic liquid crystal, swimmer trajectories are affected by layer fluctuations that ultimately lead to anomalous logarithmic tails for the transverse mean-square displacement at long times [2]. This anomalous behavior is different from what is observed for isotropic or nematic fluids, thus motivating us to extend the analysis of Ref. [2] to include the effects of complex smectic microstructures that are produced in diverse protocols. Here we discuss preliminary results, where we extend the simulations of Ref. [3, 4] to incorporate the dynamic behavior of active particles embedded in a smectic liquid crystal, with focus on the interplay between activity, flow instabilities and focal conic domains.

[1] C. Bechinger, R. di Leonardo, H. Löwen, C. Reichhardt, G. Volpe and G. Volpe, *Rev. of Mod. Phys.* **88**, 045006 (2016).

[2] C. Ferreiro-Córdova, J. Toner, H. Löwen and H. H. Wensink, *Phys. Rev. E* **97**, 062606 (2018).

[3] D. B. Liarte, M. Bierbaum, M. Zhang, B. D. Leahy, I. Cohen and J. P. Sethna, *Phys. Rev. E* **92**, 062511 (2015).

[4] D. B. Liarte, M. Bierbaum, R. A. Mosna, R. D. Kamien and J. P. Sethna, *Phys. Rev. Lett.* **116**, 147802 (2016).

P06

Turbulent and financial time series analysis

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Abstract: Some of the characteristics of turbulence are its randomness, nonlinearity, diffusivity, and dissipation, just to name few. But couldn't we characterize financial data in the same way? The answer is no, not exactly. Some of the extra descriptions for financial data, which makes it different than the steady experimental turbulence, are its Markovity and non-stationarity.

Turbulent signals:

Fig.(1) shows a non-trended noncompressible stationary turbulent velocity signal, measured in an airtank experiment in Oldenburg university. The spectrum of turbulent signals was shown by Kolmogorov to be equal to :

$$E(k) = C\epsilon^{2/3}k^{-5/3}$$

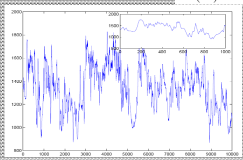

Fig. 1

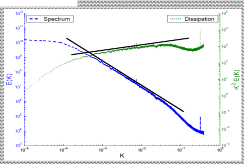

Fig. 2

where E(k) is the spectrum as a fuction of the wavenumber, C is Kolmogorov's constant, ε is the dissipation rate, and K is the wavenumber. We see clearly that the slope of the spectrum represented by the blue color in fig. (2) is equal to -5/3, while the green color represents the dissipation spectrum and its slope equals 1/3, which confirms the theory. In addition to that, the energy spectrum shows three distinct regions, namely, the large scales, the inertial range, the dissipation range and the random region. Taking a look at figs (3) and (4) we see that the same same three regions are more or less represented. First comes the Taylor microscale (λ) which is the curvature of the autocorrelation which is approximately equal for both data sets. Fig(3) data set is the same as in fig.(1) above and in fig.(4) we show another data set with a higher Reynolds number (Re=UL/ν) . We notice that in both cases the autocorrelation is finite and the zero crossing is the beginning of the random region. Fig.(3) shows the phase diagram or the bivariate probability density function of the high Reynolds number data and we notice the Gaussian mexican hat upon reaching the zero crossing point.

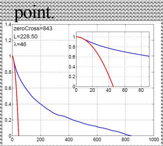

Fig.3

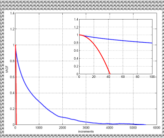

Fig.4

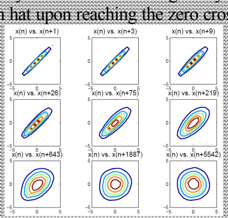

Fig.5

A useful tool in studying turbulence is the structure function or the increment and is equal to δu=|u(x+r)- u(x)|, where u is the velocity at position x, and r is the lag. The higher order structure functions which equals:

$$\langle |u(x+r)-u(x)|^p\rangle = C_p(\langle\epsilon\rangle\ r)^{p/3}$$

describes the cascading of the energy from large scales to small scales. This cascading follows a power law as is shown in the following figures.

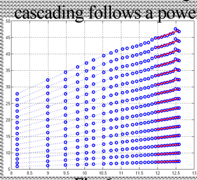

Fig.6

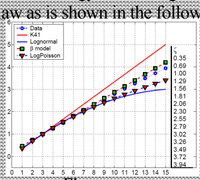

Fig.7

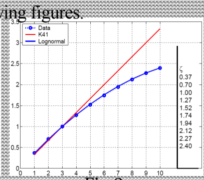

Fig.8

In fig.(6) the structure functions till the exponent p=15 were calculated and in fig.(7) we see the scaling of these structure functions according to

$$S_p(r) \sim r^{\zeta_p}$$

In fig.(7) we have used the extended self-similarity to show the power law scaling of the structure functions. We see also that the best fit is Kolmogorov's lognormal scaling model which is

$$\zeta_p = \frac{1}{3}p - \frac{1}{18}\mu\ p(p-3)$$

In fig.(8) the dissipation was fitted with the lognormal and by tunning the parameter μ one could find the best fit which is 0.24.

The question now i whether the above tools are suitable for non-stationary time series like the global warming temperatures. In figs. (9), (10), and (11) we show the temperature time seriese, the detrended temperature and the incremented temperature.

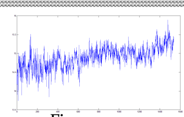

Fig.9

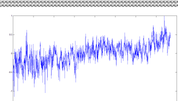

Fig.10

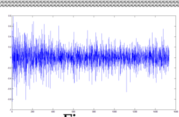

Fig.11

Financial signals:

Financial time series are non-stationary, i.e. the moments are a function of time. This is evident from fig.(12a), which is for the DAX index for the period from 16.2 till 31.12.2001. In (b) the autocorrelation function which shows a long memory. In (c) we see the spectrum which scales as -2 and not -5/3 as in the turbulent, while the probability density functions (PDFs) show anomalous scaling first and by increasing the lag they reach probably, one could say, a uniform distribution form upon reaching the zero crossing point.

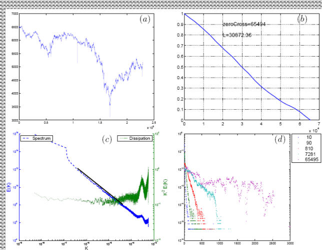

Fig.12

Non-stationary time series are modelled by a Wiener process:

$$x_t = x_{t-1} + \mu\, t + \sigma\, \eta\, \sqrt{t}$$

where x is a stochastic variable, μ is the mean (trend) of the process,σ is the variance (volatility), η is random noise, and t is the time. In fig.(13a) we show such a time series, in (b) its autocorrelation, in (c) the spectrum with two slopes -2 and -5/3 and in (d) the PDFs.

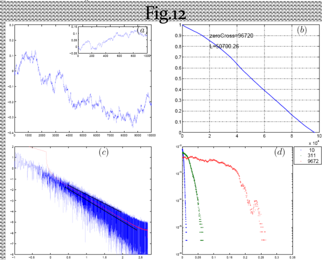

Fig.13

An important result from the above is that the tools that were used to analyze stationary turbulence are not helpful in analyzing non-stationary data, were this is evident from the plunge of the DAX data on 11.9.2001 and the spectra of both processes still show a (-2) slope.

An important tool to see the content of the spectrum of a signal in time and Fourier space is the spectrogram. In fig. (14) we see the spectrum of a sinusoid signal with two frequencies entrupted by a random band in two places, but the spectrum shows only the two frequencies. In fig. (15) we used a spectrogram to show the frequencies on the y-axis and the x-axis shows the interuption bands. Another tool is the Wigner–Ville spectrum which again shows both domains the frequency on the y-axis and time on the x-axis. Here we have used a noisy sinusoid interupted by two bands of noise. The need for other tools arises because the structure functions (the return) gives simply a random process.

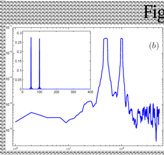

Fig.14

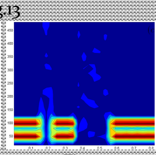

Fig.15

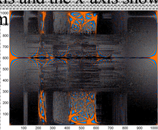

Fig.16

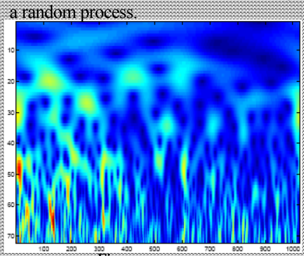

Fig.17

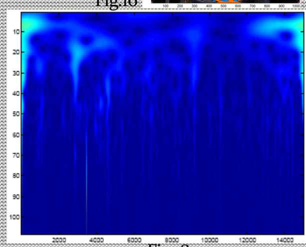

Fig.18

At last we show in figs.(17) and (18) a wavelet analysis for the signals that appeared in figs. (9) and (12a) respectively.

References:

A.N. Kolmogorov, "The local structure of turbulence in incompressible viscous fluid for very large Reynolds numbers", Dokl. Akad. Nauk. SSSR 30, 301, (1941).

J.C.R. Hunt, J.C. Vassilicos, "Kolmogorov's contributions to the physical and geometrical undertanding of small-scale turbulence and recent developments", Proceedings: Mathematical and Physical Sciences, 434, No. 1890, (Turbulence and Stochastic Process: Kolmogorov's Ideas 50 Years On), 183, (1991).

Alfred Mertins, Signal Analysis, (Wiley, 1999).

Jürgen Franke, Wolfgang Härdle, Christian Hafner, Einführung in die Statistik der Finanzmärkte, (Springer 2004).

P07

Re-entrant transitions in inertial dynamics of active Brownian particles

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This study investigates the inertial effect on the dynamics of active Brownian particles (ABP) and their long-time behavior. While numerous studies have explored the over damped dynamics of ABP, presuming that the late-time behaviors would be independent of inertia, this study of inertial ABP challenges that view. Our theoretical approach allows us to write the precise time evolution of any dynamics variable in arbitrary d-dimensions. The moment's calculation allows one to write the observables such as diffusivity, kinetic temperature, and pressure. While diffusivity was found to be independent of inertia, the kinetic temperature and pressure highly depend on inertia, even in the asymptotic limit. The steady-state velocity distribution shows a re- entrant crossover from 'passive' Gaussian to 'active' non-Gaussian as a function of inertia and activity.

[1] M. Patel, D. Chaudhuri, New J. Phys. **25**, 123048 (2023).
[2] M. Patel, D. Chaudhuri, New J. Phys. **26**, 073048 (2024).

P08

Non-Markovian model of chemical kinetics with stochastic resetting

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Studying reaction mechanisms has significant applications in biochemical processes that happen in very short lengths and a wide range of time scales. Modeling the dynamics of such processes involves a system containing colloidal particles diffusing in a potential well and it crosses a potential barrier under the influence of thermal fluctuations to form products [1]. The generalized Langevin equation has been a proven tool to give an accurate description of the non-Markovian dynamics associated with the power-law friction kernel [2]. A particle, starting from the potential minimum, escapes the well in a finite amount of time which is represented as the mean first-passage time (MFPT). In this study, we have employed the stochastic resetting [3] technique to investigate whether it is possible to change the escape process that leads to the change in MFPT. Our study suggests the particle escapes the well at a faster rate under suitable choices of reset rate and reset position. Additionally, we found the system loses its long-term memory, a well-studied phenomenon of such non-Markovian processes [3, 4], due to repeated reset at Poissonian rates. There is an optimal reset rate for which MFPT is minimum, beyond which it diverges which is a well-known feature of stochastic resetting. However, there is a very strict dependence on the reset position. Resetting the particle at the potential minimum eventually delays the escape mechanism since the system tends to stay at the stable equilibrium position for a very long duration. Therefore, the particle must be reset away from the minimum so that it can escape the well at a faster rate. In terms of energetics, reactants must be given an initial amount of kinetic energy so that they cross the barrier at a faster rate which enhances the product formation rate.

References:

1. P. W. Atkins, J. De Paula, J. Keeler, *Atkins' Physical Chemistry*. Oxford University Press, (2023).
2. W. Min, G. Luo, B. J. Cherayil, S. C. Kou, X. S. Xie, Phys. Rev. Lett. **94**, 198302 (2005)
3. M. R. Evans, S. N. Majumdar, Phys. Rev. Lett. **106**, 160601 (2011).
4. M. R. Evans, S. N. Majumdar, J. Phys. A: Math. Theor. **44,** 435001 (2011).

P09

RNA polymerase-inspired spatially truncated stochastic resetting

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Nature provides multiple avenues for stochastic resetting models – from animal search processes to population crashes caused by natural disasters. Most of the current models, however, do not account for the fact that resetting in real-life systems is constrained by energetic, spatial, or temporal factors. In this study, we introduce a refined model of RNA polymerase (RNAP) backtrack recovery that accounts for experimentally observed bias and truncation in the stochastic motion of RNAPs during transcriptional proofreading. Our model features spatially truncated stochastic resetting to an absorbing state interspersed by biased diffusion and biased random walk. Using analytical continuous space and time and Monte Carlo-based discrete space and time approaches, we compute the occupation probabilities of a particle right before it performs a stochastic reset. This statistical feature corresponds to the distribution of lengths of cleaved RNA transcripts during RNAP backtrack recovery. Bias and spatial truncation both alter the statistical features and should model the process of RNAP backtrack recovery with greater fidelity when accounted for.

[1] E. Roldan, A. Lisica, D. Sanchez-Taltavull, and S.W. Grill. Stochastic resetting in backtrack recovery by RNA polymerases. *Phys. Rev. E*, 93(6):062411, 2016.

[2] A. Lisica, C. Engel, M. Jahnel, E. Roldan, E.A. Galburt, P. Cramer, and S.W. Grill. Mechanisms of backtrack recovery by RNA polymerases I and II. *Proc Natl Acad Sci U S A*, 113(11):2946–2951, 2016.

[3] Gennaro Tucci, Andrea Gambassi, Shamik Gupta, and Edgar Roldan. Controlling particle currents with evaporation and resetting from an interval. *Phys. Rev. Res.*, 2:043138, Oct 2020.

[4] Paul C. Bressloff. Truncated stochastically switching processes. *Phys. Rev. E*, 109:024103, Feb 2024.

P10

Mathematical Modeling of Gene Regulatory Networks: Unraveling the Crosstalk Between Epithelial-Mesenchymal Transition and Pluripotency in Cancer

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The epithelial-mesenchymal transition (EMT) is a process where epithelial cells, known for their apical-basal polarity and stable connections with each other and the basal matrix, acquire mesenchymal traits. These transformed cells exhibit a fibroblast-like morphology and have increased mobility. EMT plays a crucial role in embryonic development and wound healing, as well as in diseases like cancer. In cancer, clusters of circulating tumor cells that express both epithelial and mesenchymal markers show reduced cell-cell adhesion and effective collective movement, enabling them to exit the bloodstream and invade other tissues. The transitions between epithelial, hybrid epithelial/mesenchymal, and mesenchymal states are controlled by various signaling pathways and are regulated by specific transcription factors and microRNAs. In recent years, a synergistic approach involving experiments and mathematical modeling has proposed the existence of a core regulatory network for EMT, which is present in many carcinomas. This network comprises two highly interconnected mutually inhibitory feedback loops: miR-34/SNAIL and miR-200/ZEB. We present a mathematical model of this gene regulatory network, which considers both transcriptional and translational regulation.

Stemness and cancer stem cells are pivotal in cancer progression and metastasis, contributing to tumor heterogeneity and therapy resistance. The transcription factors OCT4, SOX2, and NANOG constitute a core regulatory circuit essential for maintaining stemness. These factors not only sustain self-renewal and pluripotency but also influence EMT, enabling cancer cells to adapt and survive under diverse conditions. Based on previous models of this circuit, we developed a mathematical model that captures its key regulatory mechanisms.

In this study, we present an integrated mathematical model that combines the EMT and stemness modules into a single regulatory circuit. Using Ordinary Differential Equations, the model captures the dynamics of the OCT4, SOX2, and NANOG pluripotency circuit alongside the miR-34/SNAIL and miR-200/ZEB EMT modules. We investigate how coupling the pluripotency and EMT gene regulatory networks influences the system's stable states. Notably, the hysteresis observed in the standalone EMT module, where the mesenchymal state becomes irreversible, is altered when the circuits are coupled. This aligns with experimental evidence showing that mesenchymal cells in metastasis can disseminate to distant tissues and later revert to an epithelial phenotype to form metastatic lesions.

Our integrated model offers a framework to explore the interplay between stemness and EMT in driving cancer progression. Additionally, we highlight the role of mathematical modeling in uncovering the mechanisms underlying these processes, testing hypotheses, and guiding experimental design.

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Title: Modeling and analyzing the dynamics of glucose-insulin regulation system.

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Interaction between glycose-insulin is very important to understand the mechanisms linked to glucose dynamics in the body. Its dysfunction is not without consequences and can lead to many diseases such as anxiety, coma, vision impairments, retina microvascular connection, neuronal connections and above all diabetes [1]. The need to detect diabetic risk factors and treat diabetes-related disorders and complications has led to an increase in the number of glycoregulation models and simulation platforms designed primarily to analyze the various pathologies [2]. In this work, we study the dynamics of a glucose-insulin regulatory system at both integer and fractional order. We highlight certain differences linked to their dynamics characteristics. The numerical simulation methods used for these various analyses are those of Runge Kutta of order 4 and Grünwald-Letniko**v.** The study of the dynamics is mainly carried out by plotting bifurcation diagrams and Lyapunov maximum exponents. The resulting analysis shows chaotic behavior (presence of a disease) and periodic behavior (absence of disease). The mathematical models and algorithms used in this study reveal the harmful consequences of excess glucose on health. As part of an interdisciplinary approach combining biology, physics and mathematics, this work will contribute to a better understanding of complex systems in biology. The results obtained will make it possible not only to identify the risk factors associated with diabetes, but also to develop predictive tools and effective therapeutic strategies that will have a significant impact on public health, particularly in the following areas [3].

[1] Zimmet P, Sicree R , *Global estimates of the prevalence of diabetes for 2010 and 2030,» Diabetes Res Clin Pract,* vol. 87, (2010).

[2] Palumbo P, A. *Mathematical modeling of the glucose–insulin system:A review*. Math. Biosci., 244, 69–81. (2013).

[3] De Gaetano, A., *Mathematical modeling of diabetes progression and its implications for therapeutic intervention*. Diabetes Care. (2008).

P12

The Influence of External Periodic Perturbations on Cultural Behavior: A Google Trends Study

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This study, modified Axelrod model [1] in order to introduce periodic external fields to replicate oscillatory patterns observed in Google Trends data. By adjusting the probability B and periodicity of two fixed external fields, we approximate the temporal dynamics of search interest for specific terms, such as ”Google”, ”Excel”, ”Bundesliga” and more [2]. Curiously, our results demonstrate that the model can capture cultural patterns influenced by recurring societal cycles, such as workweek and weekend. Notably, we see that other non-periodical patterns intrinsic in other countries can be reached by randomness in the time presence of the fixed external fields. The best is the open question, why do external periodic fields, despite their simplicity, manage to reflect the complexity of collective human behavior?

[1] R. Axelrod, Journal of Conflict Resolution 41, 203 (1997).

[2] “Google trends,” https://trends.google.com (2024), https://trends.google.com.