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Overview

My research develops and leverages ideas in applied and computational mathematics to solve interdisciplinary research problems. My graduate research career includes two projects. The first uses ideas from algebraic topology and computational geometry to solve pursuit evasion problem in mobile sensor networks. My present working project leverages ideas from ergodic theory and dynamical systems to understand a novel phenomenon we call *delay-induced uncertainty*. Delayinduced uncertainty refers to a specific type of sustained temporal chaos that arises in physiological systems such as the human glucose-insulin system. Once this phenomenon is well-understood, we intend to use this understanding to improve glycemic management in the intensive care unit as well as type-2 diabetes care. These improvements will likely involve the synthesis of the dynamical systems ideas with data assimilation and machine learning techniques. In the summer of 2019 I worked with the Pacific Northeastern National Laboratory group at SAMSI. Here we were trying to solve an existing alternating current power flow problem with using machine learning approaches.

Glucose - Insulin Research

The presence of delay at multiple scales can significantly impact human physiological systems. Bhargav Karamched and collaborators have examined a novel route through which delay can cause sustained temporal chaos within concrete dynamical systems of interest in physiology and biomedicine. They call this resulting chaos delay-induced uncertainty (DIU). We believe that DIU has profound implications for oscillations that arise in systems physiology, especially the ultradian glucose-insulin oscillation observed within human endocrine physiology. Clinical medical practice rests on the assumption that medical interventions will produce predictable results. However, the presence of DIU can invalidate this assumption and thereby cause failure in proper medical diagnosis and treatment. The DIU phenomenon opens new directions of mathematical research. Its implications are not yet known to clinicians. It is vital to uncover the mechanisms that produce DIU and develop precise mathematical characterizations of the resulting dynamics. It is vital to assess the impact of DIU on data assimilation and clinical practice.

I have performed a number of computational experiments that establish the existence of DIU in the Ultradian glucose-insulin model. This model was developed to explain observed ultradian glucose-insulin oscillations in humans using a minimal number of components. It has been validated and is widely used by biomathematicians and bioinformaticists. For my computational experiments, I have designed and implemented forcing signals that model those found in the intensive care unit(ICU). In particular, I have established the presence of DIU for both a pulsatile insulin forcing drive and a step-like glucose drive wherein I sample the step heights from a particular Markov chain.

The existence of DIU in the human endocrine system may make glycemic management in ICU patients extremely difficult. In the future, I plan to show that DIU exists within actual ICU patient data, rather than models. Once this is done, we must then understand how to deal with DIU in clinical practice. Recently, artificial intelligence has been touted as a potential solution to problems in health care. My results imply that artificial intelligence may not be the solution because glucose-insulin metabolism is not just complicated but actually chaotic. A better path might be to acknowledge the chaos and approach clinical challenges statistically, estimating expected variances so that decisions can be based on the distribution of likely outcomes. Better matching of models to real ICU experience may help identify and avoid treatments that are likely to produce chaotic behavior.

Practical medicine introduces additional complexity I will analyze in future work, most notably *nonstationarity*. Thus far I have analyzed stationary models, meaning that model parameters do not

change over time. In the Ultradian context, I have therefore held the overall health state of the patient fixed, since the Ultradian model parameters represent overall health state. This is often a reasonable assumption for glycemic management in the ICU since the timescales of medical interventions are relatively fast. On longer timescales over which diseases such as diabetes affect patient health state, I anticipate that nonstationarity will be a common issue for DIU analysis in health-related physiologic settings.

I am interested in assessing the impact of DIU on the management of type-2 diabetes (T2DM). T2DM patients monitor their blood glucose levels at home in order to quantify activity impact. Here, rational decision-making requires understanding the temporal evolution of individual glucose trajectories. Glucose readings potentially become uninterpretable when DIU is present. This would render self-management a nearly impossible task and suggests that DIU may negatively impact T2DM patients. I am interested in finding ways to mitigate this negative impact.

Mobile Sensor Network Research

My mobile sensor network project has involved the development and implementation of algorithms that certify mobile coverage in minimal sensor networks. Suppose we want to detect mobile intruders inside a domain using sensors, but we cannot control the placement of the sensors. This can happen, for instance, in the context of collapsed buildings or forest fires. In such situations, a large number of of randomly placed sensors may be needed to obtain static coverage. Instead, we allow our sensors to move and show that far fewer sensors are needed for mobile coverage.

Our mobile sensing work falls into the category of *minimal* sensing problems. We assume our mobile sensors does not possess any fancy features such as GPS capability. Our sensors do not know their positions and sense only locally. Given this local information, can we determine whether or not an intruder can evade detection by the mobile sensor network? That is, can we solve the global sensing problem using only local information?

We have solved our mobile sensing problem using tools from algebraic topology and computational geometry. In particular, we have developed and implemented algorithms that compute the (random) time required for mobile coverage. Using these algorithms, we study the statistics of mobile coverage times in two dynamical scenarios. We allow the sensors to move independently (billiard dynamics and Brownian motion), or to locally coordinate their dynamics (collective animal motion models and the D'Orsogna model in particular). Our detailed simulations show, for example, that the D'Orsogna collective motion model impressively outperforms the billiard motion model.

This pursuit evasion problem has applications in various engineering fields. We have developed a few interesting questions for future research. The expected time to achieve mobile coverage decreases as we increase the number of sensors or as we increase the sensing radius. Do phase transition phenomena ever arise? In the limit as the number of sensors goes to infinity and the sensing radius of each sensor goes to zero, can one describe the asymptotics of the expected time to achieve mobile coverage? Does the distribution of this detection time converge in this limit? If it does, to what limiting distribution? How do these asymptotics depend on the model of sensor motion? I am interested in exploring how domain geometry impacts mobile sensor network performance. How do the statistics of the time at which mobile coverage is achieved change as the domain varies? For instance, what happens when a convex domain morphs into a concave domain? What can be said about collections of sensors with randomly varying sensing radii?

General Research Interest

My future research would engage in application of mathematics to various STEM fields. Not limited, but I am interested to apply my analytical provess to clinical research, quantitative biology, system biology, medicine, pharmacology, bioinformatics, engineering, etc. I strive for scientific discoveries based on clinical or laboratory data using mathematical tools. I am interested in exploring various applications of machine learning in clinical research, quantitative biology, medicine, therapeutics, pharmacology, etc. We are already aware use of machine learning in the field of neuroscience. However, I am more interested in the applications of machine learning to various human physiological systems. Using various machine learning techniques I would like to create models, develop predictions and draw statistical inferences. The quantitative biology field is growing with data everyday, I was to research about the applications of machine learning and big data and see how it benefits in performing in statistical data analysis. I believe, few years down the field of topological data analysis will have a huge impact in modelling such systems due to it's efficiency in handling various geometrical data shapes.

I wish to develop some unifying strategies that can help us better understand the dynamical features of biological systems. While it might be easy to observe what features one might incorporate while modelling a given biological system, but producing conclusive scientific results happens by knotting data to the model. This possesses a mathematical challenging problem given the data in often sparse in nature. I would like to probe into problems which can be beneficial for both inference and modelling. I wish to collaborate with scientist across disciplines and have a free exchange of scientific ideas. This would help me to formulating problems mathematically from other fields. I intend knotting the mathematical modelling and inference machinery to solve problems in clinical, quantitative biology and medicine research. I wish to take advantage of this bidirectional flows of ideas in solving problems for the advancement of the research field.