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Dissertation outline

There have been many studies on time series analysis to predict future states, to identify governing equations, and to evaluate instabilities of nonlinear dynamical systems. In addition to various methods that have been developed in the past, machine learning has also been incorporated recently. However, when the system size is large, a method to investigate dynamical properties by time series analysis has not been established yet. This thesis is devoted to developing methods to investigate properties of large chaotic experimental systems by time series analysis. To accomplish this goal, I conducted two studies.

The first study is to extend a recurrence-based method so that it can be applied to large systems. In experimental systems, the most common approach to estimating the Lyapunov exponents from time series is to regard recurrences of the time series as perturbations on its trajectories, but one cannot apply this approach to large systems. This is because the recurrence frequency decreases exponentially with increasing dimensionality of phase space. To address this problem, I focused on the fact that for a class of simple but experimentally relevant systems, the evolution of a local variable of such systems does not necessarily require a large number of variables. I found that it is sufficient to consider time series in a reduced space, composed only of such variables.

I numerically inspected this idea for systems with global or neighbor coupling. I detected recurrences in the reduced space from numerically generated time series data and estimated the parameters and functions needed to evaluate the dynamics in tangent space. After that, I evolved states and perturbations by interpolation from the given time series data and the estimated parameters and functions. By calculating the Lyapunov exponents, I demonstrated that this method is able to evaluate the Lyapunov spectrum precisely. I also argue that the studied class of systems is experimentally relevant, because well-mixed systems are often considered to be globally coupled systems, and besides, many experimental systems are known to be described by partial differential equations, which are in the scope of neighbor coupled systems.

The second study is to capture an inertial manifold from time series data using reservoir computing, which has not been possible in a reliable way by the existing methods. Here, I trained a reservoir using time series data of the Kuramoto-Sivashinsky equation (KSE) and calculated the covariant Lyapunov vectors (CLVs) of the reservoir dynamical system. I found that by checking the presence or absence of tangencies of the CLVs, the number of physical modes of the reservoir agrees with that of the KSE, except for one physical mode. I identified this missing physical mode by calculating the angles between the physical manifold of the reservoir dynamical system and the perturbations corresponding to the three symmetries of the KSE. These indicate that reservoir computing is able to capture an inertial manifold from time series data.

In this series of studies, I successfully procure the methods that can be applied to many large experimental systems, which can measure not only the Lyapunov spectrum but also the dimension of an inertial manifold. I also discuss perspectives toward applications to experimental systems and some open problems that will be a useful improvement to the proposed method in the future.