Abstract

Artificial neural networks have established themselves as a cornerstone of the modern information-centric society. In these networks, mathematically modeled neurons are intricately interconnected, and their weight parameters are trained with sophisticated methods leveraging big data. Increasing the network depth undoubtedly improves their performance, however, at the expense of a significant increase in computational time and energy consumption during the training process. In a recent paradigm shift, these networks have been materialized into physical forms, conceptualizing a physical system as an embodiment of a neural network with predetermined weights. This innovative approach, which is a departure from traditional von-Neumann architectures, circumvents the complex training process and the energy-consuming silicon-based systems. A leading methodology in this context is physical reservoir computing. There, the nonlinear transformation of input data is carried out by nonlinear phenomena in a system referred to as a "physical reservoir". The computational efficacy is deeply connected to the properties of the physical reservoir, with a plethora of promising platforms being explored.

In this thesis, we aim to propose effective strategies for *harnessing* classical and quantum systems in physical reservoir computing. Particularly, for magnetic materials, we introduce a frequency filtering protocol to achieve thermal robustness and spatiotemporal parallelization, addressing key challenges in device realization. Furthermore, to overcome the measurement back-actions inherent in quantum reservoir computing frameworks, we present a novel approach that involves feedback connections based on the outcomes of projective measurements. Our demonstrations illustrate that these methodologies significantly enhance the practicality and applicability of physical reservoir computing.

Interestingly, the diverse computational performance exhibited by various types of physical reservoirs suggests an alternative research direction; namely, examining the physical system itself through computational efficiency when employed as a physical reservoir. Here, another aim of this thesis is to develop a framework for *probing* quantum systems by expanding the paradigms of physical reservoir computing, which we call as quantum reservoir probing (QRP). In this framework, random information is locally introduced into the quantum system, and we then attempt to deduce that input from the expectation value of a local operator through

a linear transformation. The accuracy of this estimation serves as a measure of information propagation. We demonstrate that the QRP can effectively trace how information is distributed across various degrees of freedom at individual points in time. Furthermore, we observe that the dynamics of information propagation exhibit different characteristics in distinct quantum phases, serving as a marker of quantum phase transitions. The QRP method holds promise for unveiling novel insights into a broad spectrum of exotic quantum many-body phenomena.

The results in this thesis demonstrate the bi-directional application of physics for computation and computation for physics. Our theoretical contributions in this interdisciplinary field pave the way for pioneering computational techniques in physical systems, while simultaneously deepening our understanding of physical principles. We believe that the frameworks we have established for *harnessing* and *probing* nature would lay the foundation for future research endeavors in condensed matter physics, machine learning technologies, and quantum information science.