論文 / 著書情報
Article / Book Information

題目(和文)	
Title(English)	Robust Predictions with Reservoir Computing
著者(和文)	SENNCHRISTOPH
Author(English)	Christoph Walter Senn
出典(和文)	学位:博士(工学), 学位授与機関:東京工業大学, 報告番号:甲第12704号, 授与年月日:2024年3月26日, 学位の種別:課程博士, 審査員:熊澤 逸夫,山口 雅浩,小尾 高史,篠崎 隆宏,渡辺 義浩
Citation(English)	Degree:Doctor (Engineering), Conferring organization: Tokyo Institute of Technology, Report number:甲第12704号, Conferred date:2024/3/26, Degree Type:Course doctor, Examiner:,,,,
学位種別(和文)	博士論文
Category(English)	Doctoral Thesis
種別(和文)	論文要旨
Type(English)	Summary

（博士課程）
Doctoral Program

論 文 要 旨

THESIS SUMMARY

系・コース： Department of, Graduate major in	Information and Communications Engineering 系 Information and Communications Engineering コース	申請学位（専攻分野）： Academic Degree Requested	博士 Doctor of (Engineering)
学生氏名： Student's Name	Senn Christoph	指導教員（主）： Academic Supervisor(main)	Kumazawa Itsuo
		指導教員（副）： Academic Supervisor(sub)	

要旨（英文 800 語程度）
Thesis Summary（approx.800 English Words ）

The dissertation "Robust Predictions with Reservoir Computing" consists of 5 chapters and is structured as follows.

In the introduction (Chapter 1) we present the background and the motivation for our research and discuss some recent applications of reservoir computing. The goal of our research is to increase the robustness of reservoir computing and apply it to real-world scenarios.

This is followed by Reservoir Computing (Chapter 2). We introduce the basic notions of reservoir computing for virtual and physical systems. In addition, recent literature, with a focus on applications, is introduced. Special focus is given to mass-spring networks as a general computational model for physical reservoir computing. By connecting multiple masses with non-linear springs, applying force as input to specific masses and recording the acceleration of the masses we can create a simple system, capable of doing predictions. We then propose a physical reservoir computing system based on conductive fabric and examine its memory capacity in particular.

In Abstract Reservoir Computing (Chapter 3), we propose a novel training approach, suitable for virtual and simulated physical systems, based on abstract interpretation. When testing the robustness, a common approach is to create perturbed inputs by sampling around the original input. Using this, or similar approaches that rely on creating perturbed inputs, we have to calculate the output for each perturbed input separately, which can become infeasible for large numbers of perturbed inputs. To alleviate this, recently, a technique called abstract interpretation has found its way into deep learning. By creating sets consisting of the possible inputs, we can compute the set of possible outputs, and directly test if our model behaves as expected, i.e., if the output is within the expected boundaries. By applying this idea to the training of reservoir computing systems, we derive an "abstract regularizer" which increases the robustness against noise for virtual and physical systems. Using different datasets of different difficulty, we show that physical systems trained this way are potentially more robustness against different sources of noise.

Then in SwarmESN (Chapter 4), we show how reservoir computing can be used for distributed anomaly detection. Based on a benchmark dataset with multiple sensor readings, we create a reservoir for each sensor, and feed it its values. We then devise a way to share network states between the reservoirs, to mix local and global information. Then each reservoir creates a prediction about the global state (e.g., if we are in an anomalous state or not). This is applied in a setting where the nature of the setup and real-time constraints, make a centralized processing system is infeasible. Thus, a distributed system is necessary.

We explain how such a reservoir computing system, with online learning capabilities, can be realized, while also considering hardware constraints, i.e., implementation on FPGAs.

In Conclusions and Future Work (Chapter 5) we give a conclusion of this thesis and give some ideas for future research endeavours. Reservoir computing, especially physical reservoir computing, is promising for the future of computation due to its energy efficiency, and we hope to have helped to push the field forward with this work.