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Interferometric stabilisation of a fibre-based optical computer

Experimental study

Mémoire présenté en vue de l'obtention du diplôme
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Abstract

Acknowledgements

Contents

List of Figures

Chapter 1

Introduction

For the past few years, interest in optical data processing devices has been increasing. Their main advantage over silicon-based computers is that they are intrinsically faster because the information is carried around at nearly the speed of light, which could allow to overcome the limit in processing speed soon to be reached by classical integrated circuit electronics.

This Master thesis tackles the implementation of an optical computer based on reservoir computing.

Chapter 2

Reservoir Computing

2.1 Introduction

Reservoir Computing (RC) is a bio-inspired artificial recurrent neural network which is based on the Echo State Network (ESN) paradigm introduced by Herbert Jaeger in [3]. This computation scheme is well suited for real-time data processing and for chaotic time series prediction[3, 4, 6], and achieves state of the art performances in those domains, as well as in speech recognition[9, 8, 5], nonlinear channel equalisation[3] and financial forecasting [1].

A Reservoir Computer (RC) is made of a large ensemble of interconnected neurons, which are merely entities carrying an activation level. The activation level is updated according to the connection weights of the reservoir, or *synaptic matrix* as it is referred to in the field of neural networks, and with a nonlinear function, called the *activation function*. The nonlinear character is one of the main features making neural networks so powerful. Moreover, with a proper activation function, one can reach a saturation state, which mimics the behaviour of biological neurons. This is traditionally achieved using the *sigmoid* function. Those principles are introduced in [2, p.227-228] and in [7, p.727-728].

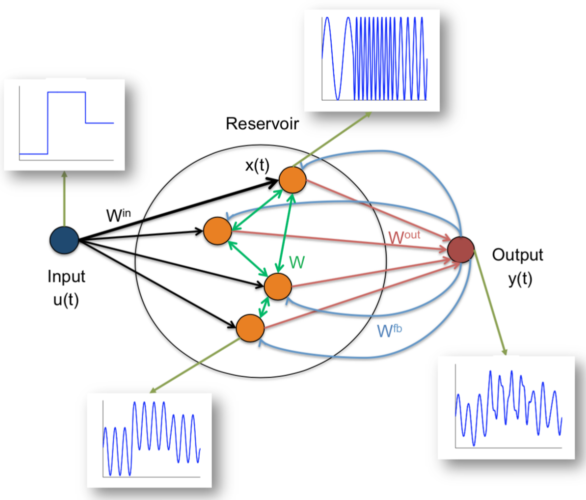

Figure 2.1: Principle scheme of a RC [1]

The activation level of the neurons making up the reservoir characterise its state, which is time-dependent object. The neurons are interconnected in such a way that they influence the dynamic of each other, leading to a complicated evolution the state of the reservoir. What a first glance may seem to be a mathematical nightmare turns out to be the main advantage of RC, making it so powerful. Indeed, by making the connection matrix as messy as possible, *i.e.* by using randomness, breaking symmetries,... one notices that the effect of such a reservoir, when being fed a time-dependent signal, is to map it to a higher-dimensional functional space, the dimensionality being determined by the intrinsic dynamics of the neurons and depending on the richness of the connection matrix. Its link to ESN provides RC with another advantage compared to other computation schemes, namely it has a memory of the input, thanks to the fact that the neurons are *echoing* the effect of the input to one another. The output of the reservoir is obtained by adequately combining the neurons using the output matrix. These notions are summarised at the Figure 2.1.

Chapter 3

Optical RC with frequency multiplexed neurons

Chapter 4

Interferometric stabilisation of RC optical resonator

Chapter 5

Results

Chapter 6

Conclusion

Acronyms

ESN Echo State Network 7, 8

RC Reservoir Computer 4, 5, 7, 9, 10

RC Reservoir Computing 4, 7, 8

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