OPTICAL RESERVOIR COMPUTING: PROSPECTS OF USING SUB-10 PICOSECOND LASERS

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Abstract. *Training neural networks is hard. The industry is approaching the limits of silicon-based computing, both in terms of transistor size and chip dimensions. There are already examples of technologies that allow computations without using silicon. A paradigm for machine learning that could have enough representational power also exists. It is Reservoir Computing, which is also quite amenable for adaptation on non-silicon-based computing devices. In this work, I propose a specific type of laser-based reservoir computing scheme that builds on, and should improve, the existing solutions.*

Keywords*: reservoir computing, machine learning, optical computing, InGaN lasers.*

Introduction

In recent years machine learning took off as a powerful tool for solving all sorts of problems that require cognition. From drug discovery [1] and simulations [2], to computer vision [3] and natural language processing [4], machine learning, and more specifically deep learning, has proven to be an invaluable tool with superior capabilities.

But there are problems with the existing approach, namely with the foundation of existing solutions. All recent advances in deep learning are mainly due to the explosive growth in computational power of GPUs and other accelerators. But as we approach the limits of transistor sizes and chip sizes [5], it becomes less and less efficient to train and run neural networks.

Given the current state of ecological and economic affairs, efficiency is paramount. If we want to solve our compute efficiency crisis, we need to reinvent the computing devices. There are already massive developments in the fields of quantum, optical and graphene-based computing, all with promising results and a fair share of current problems. Off all three, optical-based computing seems the most promising in the short to medium term. It is better understood than the other two, and for specific tasks, already outperforms both classic silicon-based chips and quantum chips and accelerators in terms of efficiency.

When it comes to deep learning or machine learning in general, efficiency is especially important. Current methods have a massive carbon footprint [6] and given the whole activeness of the domain, it is an ecological problem. A method similar to deep learning is reservoir computing, that for specific tasks is on par with the former, with significantly easier training process.[7]. Reservoir computing generally refers to the family of algorithms and methods that feed input into a so-called reservoir, a fixed random dynamic system, and then only the readout mechanism is adapted so that it outputs meaningful values. Because the reservoir does not need to be trained, only the output layer, these systems are significantly easier and faster to train than a deep learning system. A drawback is that a neural network has still much more representation power, due to the possibility to learn all the internal parameters. But this problem can be partially overcome by having a significantly bigger reservoir. Another nice thing about reservoir computing is that the reservoir itself can be implemented as a non-silicon-based component, for example, it can be laser-based. A match made in heaven.

There are already existing prototypes of reservoir computing-based systems using optics or lasers.[8, 9]. The main drawback of all of these are high latency and expensive hardware needed for the systems to run. There even exist optics-based systems that try to do deep learning.
The rest of this paper is structured the following way: first, we describe the proposed method, using a sub-10 picoseconds InGaN laser. Then we discuss possible applications and future developments.

Methods

The system is based on a sub-10-picosecond blue-violet InGaN two-section laser [10], a reservoir made of passive diffractive optical components, based on the all-optical diffractive deep neural network [11] and a readout mechanism, made of a sensor and interpreter. The readout interpreter must be trained, therefore for convenience, it is done on a classic computer.

The core idea is to have the signal encoded as laser pulses that go through the reservoir and on the output the light is recorded by the sensor that passes the converted signal into the computer for interpretation.

The reservoir, based on the design described in [11] could be easily 3D-printed, allowing for easy manufacture. It represents the nodes in the reservoir as points on a given transmissive (or reflective) layer with a complex-valued transmission (or reflection) coefficient. The weights in the reservoir are based on free-space diffraction and determine the interference of the secondary waves that are phase- and/or amplitude-modulated by the previous layers. These are randomly specified before being materialized in the 3D-printed component.

To achieve overall low latency în the system, the modulator, used to encode necessary information into the light emitted by the laser, aș well aș the readout mechanism must be implemented using FPGAs. These would allow tuning the classical computing architecture to keep up with the optical component. Of course, this would be the bottleneck of the system, that's why a further stage would be to have an all-optical system.

Conclusions

This work outlines the current state of affairs in efficient machine learning and gives a brief overview of advances in non-silicon based solutions. The proposed method can be seen as an efficient alternative to existing ways of deploying and operating deep neural networks, especially for domains working with time series and with sensitive latency requirements. Based on the proposed idea, experiments must be conducted to validate it. We believe that the work presented in this paper provides a new application for the now experimental sub 10 ps pulse devices.

Acknowledgements.

This work is supported by the project 20.80009.5007.08 Also I would like to express my gratitude to Vasile Tronciu for guidance în the matters of lasers science.

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