Real-Time Implementation of a Retinal Model

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Abstract

Vision systems in biological entities are one of the most complex sensory inputs in nature. If we want to simulate them, it would require incredible amounts of computing power and, traditionally, several algorithms to perform each individual task. A parallel computation platform is the best way to go while attempting to solve this problem, since neural structures in the brain compute in this way.

SpiNNaker is one of such platforms, a network of low-powered processing units, each of which can simulate several neurons. Given that the SpiNNaker platform resembles this natural neural structures, computer vision algorithms need to be developed in a completely different manner.

The aim of this project is to develop algorithms in the realm of computer vision but using a spiking neural networks approach. In particular we'll study time-based spike codes and how to process them. This algorithms should be able to cooperate and share their interpretation of the input data to gain a more robust understanding of images.

1. Introduction

In recent years neuromorphic (i.e. one that mimics the brain) hardware has risen attention as a different way of computing. One key aspect is the high parallelism found in the infrastructure of the brain. Platforms such as SpiNNaker [5] emulate such parallelism; furthermore it does so while maintaining low power consumption. The SpiNNaker platform can also give neural simulations the flexibility of software models and keep them running in biological real-time.

Converting conventional images or video into spike based representation is a must-do step for further studies, in section 4 we report on the work done so far towards this goal. From this data we'll develop learning and classification algorithms. Furthermore this algorithms may lead to an implementation of vision tasks such as registration or optical flow.

2. Research Aims and Contribution

This research aims to develop computer vision algorithms using SpiNNaker. This is to be achieved by modelling biological vision, using spiking neural networks, on SpiNNaker. Several stages of vision would need modelling and/or implementation, the latter has been the goal for this year's work. We hypothesize that a better understanding of vision in biology will lead to a unified computer vision framework. Using neural networks should translate in gaining an insight to the meaning of elements in a scene and, thus, a relation between different images of the same scenario.

Bio-inspired vision algorithms using SpiNNaker hardware could be used on robotics, security or transportation applications. The research on learning and classification could lead into a theory of learning and memory in the brain.

3. Previous Work

In order to process visual input from frame based imaging devices on a spiking neural network (SNN) a transformation is needed. The most common way is to simply encode using Poisson spiking with a

rate that is proportional to pixel intensity. This is not entirely accurate as cells in the retina react to changes in intensity[1]. One of the most accurate retinal models was developed by Wohrer and Kornprobst in [6]. A special category is hardware based bio-inspired retinas. First reported on [4]. New devices have been developed and reported in [2, 3], this are splendid real-time, low-powered, high-dynamic-range event-based cameras; though they have limited availability.

4. Project Progress to Date

The literature review is about 60%, though further reading might prove that this number might change. Converting DVS emu Converting BASAB model GPU, SPINNAKER, video transfer Paper on MNIST

5. Thesis Outline

- Abstract
- Chapter 1. Introduction.
 - Neural networks.
 - Spike codes in vision.
 - Inhibition.
 - Spatio-temporal patterns and learning.
 - Research objectives.
- Chapter 2. Background.
 - SpiNNaker platform.
 - Real-time artificial neural computations.
 - Polychronization.
 - Classification.
- Chapter 3. Methodology.

- Model visual input using time-based spike codes.
- Hierarchical networks for robust classification.
- Feature identification.
- Sensor fusion and image registration.
- Chapter 4. Results.
 - Comparison with other methods.
 - Discussion.
- Chapter 5. Conclusions and Further Work.
 - Conclusions.
 - Future work.
 - Publications.
- References.

6. Conclusions and further work

Obtained further knowledge about basic anatomy of the eye from a functional approach. Importance of mutual inhibition to enable high efficiency computing in the brain and robustness of neural structure.

Real-time, although with low temporal resolution, is achievable with common GPU and the right combination of mathematics and engineering. Memory reads and writes in a GPU is extremely important; it might be one of the biggest constraints of the presented algorithms.

We established a timing mechanism to emit spikes from a rank-ordered source. Possible solutions for a faster mutual inhibition algorithm might be to do it in-line as we send spikes to neuromorphic hardware; or let the neural simulation deal with mutual inhibition.

To reduce the power consumption/hardware requirements for mobile applications the best way to go might be change the resolution so not all image is perceived in high resolution.

7. Publications

Part of the work carried during this year will be published as a paper on a **Frontiers in Neuroscience** journal special issue "Benchmarks and Challenges for Neuromorphic Engineering".

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Acknowledgements

This research is funded by the National Council of Science and Technology (CONACyT) and the Secretariat of Public Education (SEP) of México.

A. Project Plan

