

SpiNNaker-based Visual Systems

End-of-first-year report

Garibaldi Pineda García

Supervisor: Steve Furber

Co-supervisor: Dave Lester

Advanced Processing Technologies Group
School of Computer Science
University of Manchester
United Kingdom



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Chapter 1

Introduction

A picture is worth a thousand words
Frederick R. Barnard - 1921

Why vision why spinnaker what do I want to do why is that important

1.1 Vision

Most animals use some kind of visual input
It remains the best way for some tasks

1.2 Eyes for computers

different types of camera technologies

1.3 Common cameras as spike train sources

Why using cheap/common cameras to translate to spikes is useful

Chapter 2

A look into the brain

2.1 The brain

The brain is an exquisite piece of biological computation

evolved from few neurons into the cortex

It consists of around 100 million neurons interconnected through 100 billion synapses

It can perform the most diverse tasks, from bird spotting to mathematics to music

All of this with high efficiency

2.2 Neurons and responses

Neurons are small cells composed of a soma (body), dendritic and axonal tree for communication

Theories suggest they perform some kind of calculation, most of the time modelled as a threshold activation function

Latest evidence suggests that they communicate through spikes, on-off responses

2.3 Different languages

Neurons communicate using different “languages”, spike-codes

rate time rank-order

Input from sensors is most likely rate-based, though processing time and energy consumption in the brain suggests a different one is used for further processing

2.4 Artificial neural networks

First modelled as an on-off threshold gate, perceptron

Multi-layered networks and feedback, Hebbian learning

Spiking neural networks, third gen, include time as a factor, more accurate, more powerful mathematical properties,

learning studied using Hebbian back-prop, stdp, bcm

still work to be done on time-based learning

2.5 Conclusions

conclusions the brain

Chapter 3

Neuromorphic trends

3.1 Classical computing

classical computing

3.2 Neuromorphic trends

neuromorphic hardware trends

3.3 SpiNNaker

spinnaker info

3.4 Event-based model

event-based programming/infrastructure

3.5 Conclusions

conclusions neuro hardware

Chapter 4

The eye and the retina

4.1 The eye and it's structure

There are different examples of eyes in nature

- The mammalian eye consists of lens/body/film
- film is the retina

4.2 Retinal models

Cell-by-cell modelling

- Functional modelling

- Mutual inhibition is embedded

4.3 Transmission and processing efficiency

Output should be a sparse representation if we hope to keep with biological plausability

- Time for processing is a big issue

4.4 Conclusions

conclusions retinal models

Chapter 5

From images to spikes

5.1 Real-time encoding

real-time encoding

5.2 SpiNNaker implementation

spinnaker encoding

5.3 Dataset creation

dataset for article

5.4 Conclusions

conclusions rank-ordered images

Chapter 6

Conclusions and plans

6.1 Conclusion**6.2 Further work****6.3 Plans for second and third year**

Bibliography