

Hierarchical architectures for spiking Winner-Take-All networks

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Outline

1 Introduction

2 Experiments

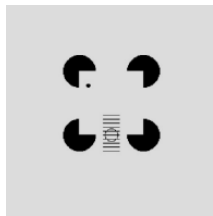
3 Results

Introduction

- Spiking vs common NN (energy efficient, more biologically plausible)
- Importance of hierarchical architectures
- Goals of this thesis
 - Simulate feedback in the visual cortex
 - Show connection between Bayesian inference and network model

Biological background

- Winner-Take-All networks
- Modular structure of the brain
- Hierarchical structure of the brain
- Feedback mechanisms in cortical hierarchies



Kanizsa square, Lee TS (2003)

Biological background

- Probabilistic brain
- Synaptic plasticity
- Spiking neural networks
- Winner-Take-All networks

Theoretical background

- Bayesian inference and its relevance to neural networks
- Explain model... (input image, input neurons, output neurons, prior neurons, spikes, doubleexpo kernel, membrane potential, firing rates (poisson, $e^{u - i(t)}$), adaptive inhibition... !!!AM BESTEN MIT DER ZEICHNUNG ERKLÄREN!
- Nessler said that: Every synaptic weight converges to the log of the conditional probability that the presynaptic neuron has fired just before the postsynaptic neuron, given that the postsynaptic neuron fires. Proven later in Experiment

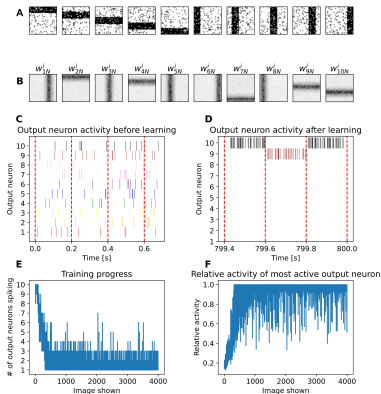
Methodology

- Simulation was performed in Python
- Simulation step size was 1 ms
- Pixels of input images and the prior had a noise level of 10%

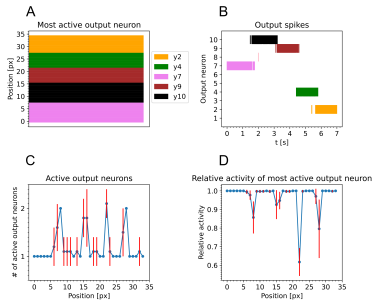
Ambiguous visual stimuli 1

- Network learned to group horizontal and vertical bars into 10 groups
- After training ambiguous images with 1 horizontal and 1 vertical bar were shown
- Network was able to focus on individual bars, due to prior neurons

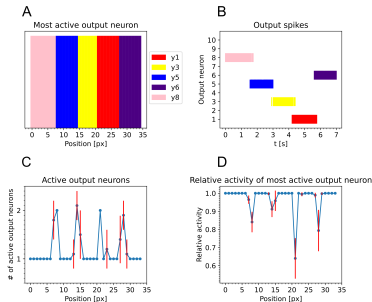
Ambiguous visual stimuli 2



Ambiguous visual stimuli 3

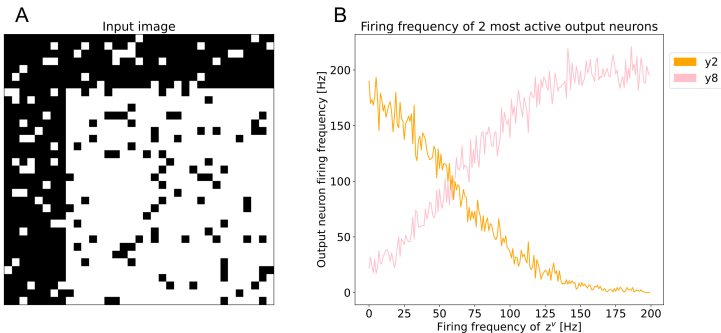


Horizontal validation



Vertical validation

Ambiguous visual stimuli 4

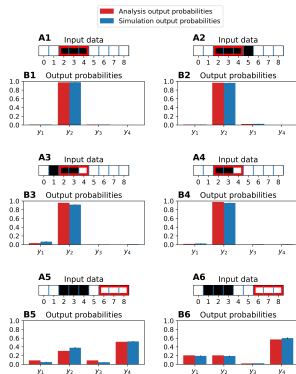


Variable prior activity

Mathematical analysis and simulation of the network 1

- usage of smaller 1-D images to make network easier to analyse
- Mathematical derivation of Bayesian likelihood, prior and posterior
- Derived synaptic weights from Bayesian likelihood and prior
- Simulated network with those weights and fitted hyperparameters
- Compared Bayesian posterior to output of the simulation

Mathematical analysis and simulation of the network 2



Kullback-Leibler divergence = 0.0101 ± 0.0009

Conclusion

- Biological effects could be reproduced
- Connection between model and Bayesian Inference was shown
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Sources

- Lee TS, Mumford D. (July 2003). “Hierarchical Bayesian inference in the visual cortex.” In: J Opt Soc Am A Opt Image Sci Vis. DOI: doi:10.1364/josaa.20.001434



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