An efficient coding interpretation of early visual and auditory processing

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Machine learning to human learning series

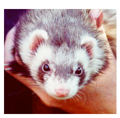
A case study for context

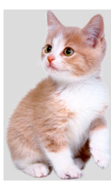
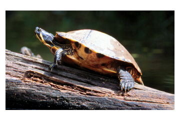
Early visual and auditory system coding

- Classic/traditional neuroscience
  - traditional neuroscience can answer "what" a neuron responds to by correlating activity with a stimulus
  - Understanding visual and auditory coding this way shows disparate, complicated systems
- Efficient coding approaches parsimoniously explain visual and auditory coding
  - Answering the question "why" these responses
  - Both systems perform the same computation
  - That strategy, btw, also useful to engineers!

Universal coding principles

At the sensory processing level we are discussing today, the neural code is well-conserved among these animals

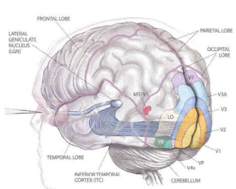



Let's begin with low-level visual coding

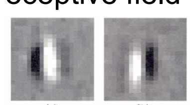
Thalamocortical visual pathway

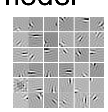

Frisby, 1979



Retina → LGN ⇄ V1

V1 simple cell receptive field model





Selective for:

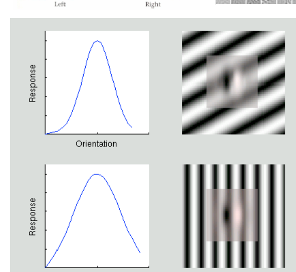
Position

Orientation

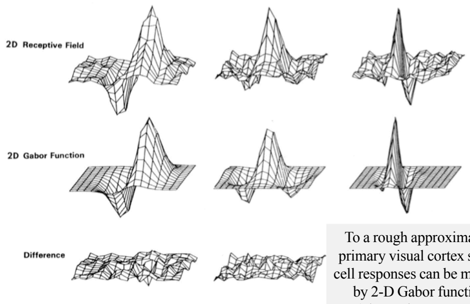
Spatial Frequency

Phase

Direction of Motion
(not discussed here)



Gabor wavelet description

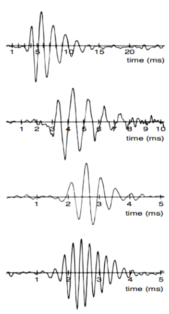


(Jones & Palmer 1987)

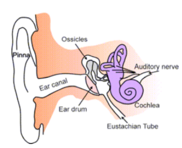
To a rough approximation, primary visual cortex simple cell responses can be modeled by 2-D Gabor functions (planar sine waves in a gaussian envelope)

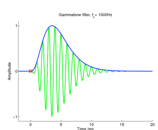
The low-level auditory code...

Auditory nerve filters



deBoer and deJongh, 1978





Approximated by gammatone functions (a sinusoid in a gamma function envelope)

Levels of understanding

V1 simple cells ⟷ 2D Gabor wavelets

Auditory nerve ⟷ Gammatone filters

One major question remains...

How does the brain achieve this? (for another day)

<u>Why?</u> <u>What is the goal of this coding scheme?</u>

Efficient coding Hypothesis

The visual system can be understood using different levels of analysis.

<u>Marr's level of analysis:</u>

1. Hardware, implementation
2. Representation, algorithm
3. Computational Theory

Most neural network approaches

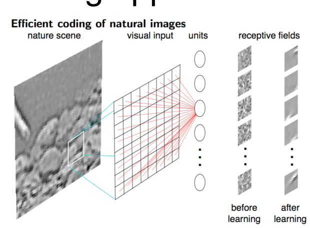
The goal of early sensory systems is to reduce the amount of redundancy in the neural code
(Attneave '54, Barlow '69)

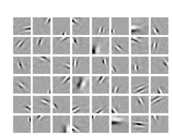
Efficient coding approaches

<u>Ecological goal</u>:

Efficiently encode signals of our natural environment

Natural images
Natural sounds



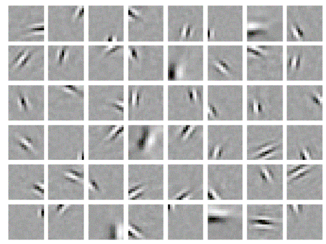


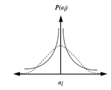
A Tale of Two Coding Strategies

Two of many related strategies.

Note, the following two can also be related mathematically, even if presented in a conceptually distinct way.

Sparse Coding Hypothesis

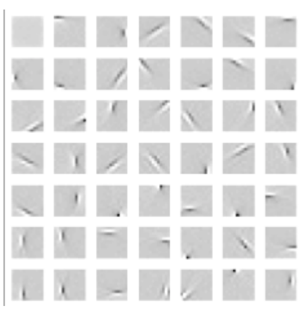




Minimize # of active neurons while still representing the image (Olshausen & Field '96)

Advantages: metabolically efficient (Neural action potentials are expensive)

Independent Coding Hypothesis



$p(f_1, f_2) = p(f_1)\, p(f_2)$

Make the neural filter responses as statistically independent as possible, while still representing the image. (Bell, Sejnowski '97)

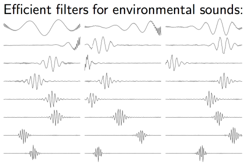
Related conceptually to the Blind Source Separation problem (cocktail party demo)

Efficient coding: auditory system

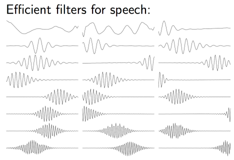
- If the efficient coding principle is true, we can use the same algorithms with only a change in inputs!
  - Vectors represent sound intensity (vs luminance)
  - Use natural sounds instead of natural visual scenes
  - So what does an efficient auditory system look like using the same coding strategy?
    - Depends on what you use as a "natural sound"

The derived code depends on the signal

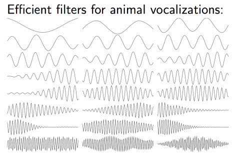
Efficient filters for environmental sounds:



Efficient filters for speech:



Efficient filters for animal vocalizations:



The Implication

The early visual and auditory systems are performing a very similar function, differing primarily in their inputs

Review: early visual and auditory system coding

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  - traditional neuroscience can answer “what” a neuron responds to by correlating activity with a stimulus
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A new story about neural processing

“Some people say we only use 10% of our brains...
I'm trying to get mine down to 5.”
- David Field, Dept of Psychology, Cornell

A commentary on traditional “correlation-driven” neuroscience

What makes primary visual cortex most active?
A series of randomly oriented lines
So is it the “line-processing area”? That's misleading at best.
What is it “for”?
Efficient early visual processing

Conclusion: Comp Neuro can...

- Bridge disparate fields of research
  - e.g. auditory and visual processing
- Provide testable, compact descriptions of neural processing
  - “sparse coding” vs Gabor wavelet statistics
  - A way to avoid the V2 career graveyard?
- Directly relate processing in the brain to current engineering approaches
  - e.g. ICA used in V1 and auditory research is also used for solving the blind source separation problem

Extra slides:

If there is time, these slides explain my specific contribution to the field of efficient coding which I may use for reference in a brief explanation

Applications...

- Armed with a high-level computational understanding of the visual and auditory systems, what can we do?
- Predict the nature of spontaneous activity in the developing brain (plug for my research)

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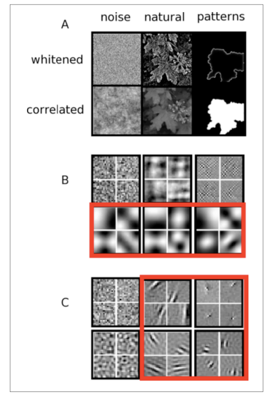
Higher-order statistics are critical in development

Adult V1 coding models rely on higher-order statistical structure

The majority of V1 developmental models ignore this structure

The approach here uniquely shows that an efficient coding approach can be effectively applied to understand visual development



A: image classes

B: Correlation-based receptive fields (PCA)

C: Rfs from higher-order statistical approach (ICA)

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Flipping the question...

Traditionally, we would ask
“How does the visual system develop?”

Now, instead, we can ask
“How *should* the visual system develop”
and match our predictions to reality

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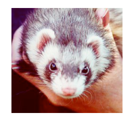
Ubiquity of retinal waves

(Feller et al 1996)

(Galli & Maffei 1988)



(Feller et al. 1996)

(Catsicas et al. 1998, Wong 1998)

(Warland et al. 2006)

(Meister et al. 1991)

(Sernagor & Grzywacz 1993)

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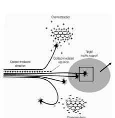
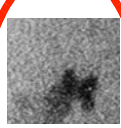
Developmental Strategies of Innate Learning in the Early Visual System





Innate: prior to visual experience

Learned: activity-based refinement, as done by natural experience

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Motivation

The principle of innate learning: spontaneous patterns of neural activity are used to train or refine a sensory system in an analogous way to how the system can adapt based on natural experience.

Main advantage: Parsimony

	Pre eye-opening	Post eye-opening
Neural activity	Spontaneous Activity	Visual experience
Algorithm	Activity-based refinement	Learning

Activity-based learning (e.g. efficient coding here)

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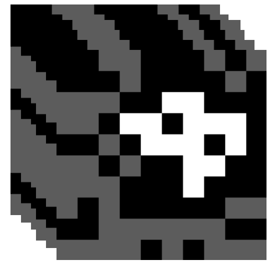
How to generate patterns?

- Consider a pattern generator that
  - Is decentralized (and conceptually simple)
  - Relies solely on local interactions
  - Has similar statistical structure across multiple scales

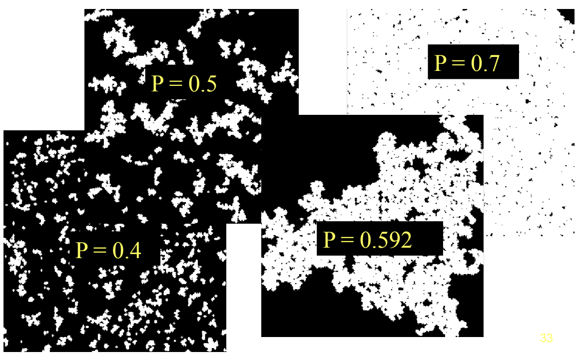
Percolation models!

First step to generating self-similar patterns

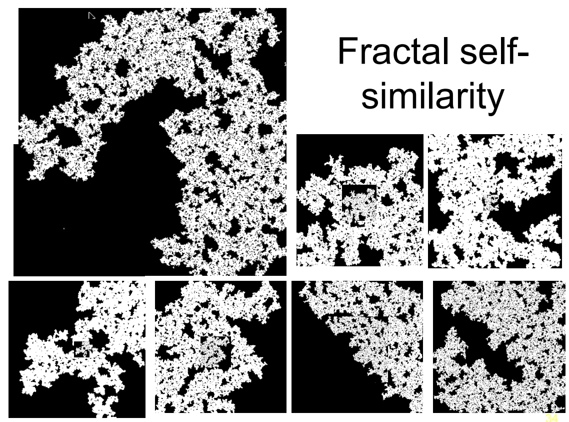
Percolation Clusters - example: p = 0.5



Percolation clusters vs. p

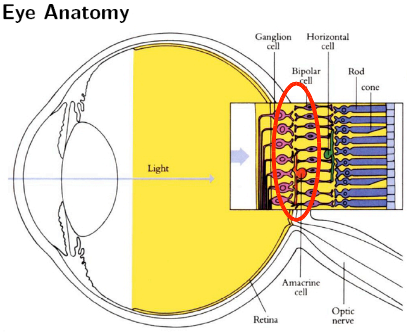


Fractal self-similarity



The Retina - biology of retinal waves

Eye Anatomy



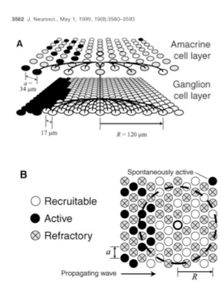
Layers:

Amacrine Cells

Ganglion Cells

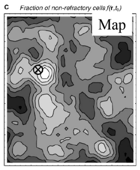
Retinal Wave Model (Butts et al. 1999)

(In red: related parameters in the 3-parameter pattern generation)



Amacrine cell layer
- Cells in one of three states
- Random, spontaneous firing
- Wave propagation by thresholded local pooling
  - Limited by dendritic field size (like 'r' in our technique)
  - Threshold neighbors for excitation (like 't' in our technique)

Retinal Wave Model – fraction of recruitable cells

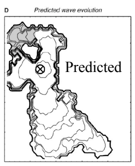


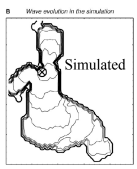
Instantaneous wave propagation depends upon a single parameter:

the fraction of recruitable amacrine cells.

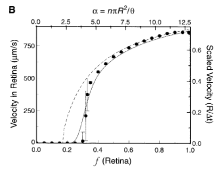
Similar to 'p' in our technique

Note: this is a by-product in the Butts model, but a fixed parameter in our generated patterns.





Wave speed vs. "p"



(Butts, Feller, Shatz, Rokhsar 1999)

Figure 3. Wavefront velocity is governed by a single parameter. A.

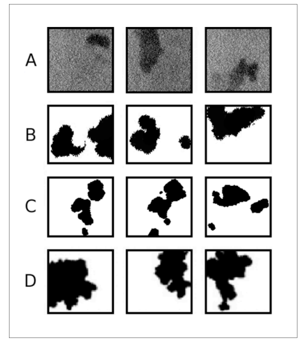
The result: images of spontaneous activity

Experimental waves, ferret
(Feller et al 1996)

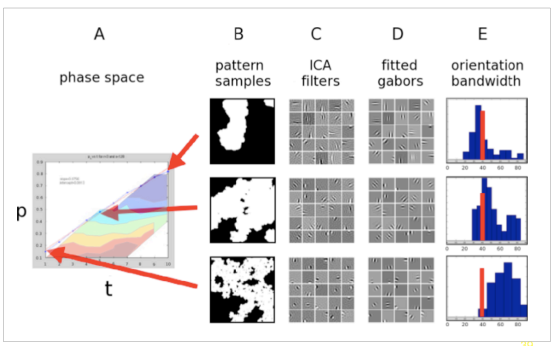
Model waves
(Butts et al 1999)

Model wave extent
(Godfrey & Swindale 2007)

Pattern wave extent
(Albert, Schnabel, Field 2008)
(p = 0.55, r = 3, t = 6)



Example: receptive field variation



Conclusions

This monocular model uniquely demonstrated that simple patterns of activity can be used to train physiologically relevant cells in an efficient coding paradigm.

This approach can be used to make predictions on the nature of the spontaneous neural activity prior to eye opening

	Pre eye-opening	Post eye-opening
Neural activity	Spontaneous Activity	Visual experience
Algorithm	Activity-based learning (e.g. efficient coding here)	

The principle of innate learning: spontaneous patterns of neural activity are used to train or refine a sensory system in an analogous way to how the system can adapt based on natural experience.

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