The "What" Pathway And the Fast Fourier Transform

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Overview

- The "What" Pathway
- Capsules
- Information Entropy
- The Fast Fourier Transform (FFT)
- The FFT and the "What" Pathway

The What Pathway

- V1 --encodes the image in terms of oriented edge detectors that respond to edges along different angles of orientation.
- V2 -- encodes combinations of edge detectors to develop a vocabulary of intersections and junctions, along with many other basic visual features
- V4 -- detects more complex shape features, over an even larger range of locations (and sizes, angles, etc).
- **IT-posterior** (PIT) -- detects entire object shapes, over a wide range of locations, sizes, and angles.
- IT-anterior (AIT) -- this is where visual information becomes extremely abstract and semantic in nature -- it can encode all manner of important information about different people, places and things.





The What Pathway



V1 simple cell edge detector



LGN



Figure 6.2: How the retina compresses information by only responding to areas of contrasting illumination, not solid uniform illumination. The response properties of retinal cells can be summarized by these Difference-of-Gaussian (DoG) filters, with a narrow central region and a wider surround (also called center-surround receptive fields). The excitatory and inhibitory components exactly cancel when both are uniformly illuminated, but when light falls more on the center vs. the surround (or vice-versa), they respond, as illustrated with an edge where illumination transitions between darker and lighter.

Capsules

- Modules
- Contour interpolation: A case study in Modularity of Mind
 - Keane, Brian P
 - Jeffrey Fodor



Capsules

- Geoffrey Hinton
- Max Pooling is terrible
- Encode More Information





Capsules





Capsule vs. Traditional Neuron			
Input from low-level capsule/neuron		$\operatorname{vector}(\mathbf{u}_i)$	$\operatorname{scalar}(x_i)$
	Affine Transform	$ig \widehat{\mathbf{u}}_{j i} = \mathbf{W}_{ij}\mathbf{u}_i$	_
Operation	Weighting	$ \mathbf{s}_j = \sum_i c_{ij} \widehat{\mathbf{u}}_{j i} $	$\left \begin{array}{c} a_j = \sum_i w_i x_i + b \end{array} \right $
	Sum		
	Nonlinear Activation	$\left \ \mathbf{v}_j = rac{\ \mathbf{s}_j\ ^2}{1+\ \mathbf{s}_j\ ^2} rac{\mathbf{s}_j}{\ \mathbf{s}_j\ } ight.$	$h_j = f(a_j)$
Output		$ $ vector (\mathbf{v}_j)	$\operatorname{scalar}(h_j)$



Information Entropy

- "Humans and Deep Networks Largely Agree on Which Kinds of Variation Make Object Recognition Harder"
 - Kheradpisheh, Saeed R. et al
 - August 2016
- Compared Humans and DCNN (Deep Convolutional Neural Net)
- The three-dimensional object models are constructed by O'Reilly et al. (2013)
- Humans and Computers Agree

Information Entropy

Entropy Examples





H = 2.0 bits

H = 2.0 bits





H = 1.0 bits

H = 0.3 bits



H = 1.9 bits



H = 0.0 bits



Information Entropy



FFT



- "Differences in velocity-information processing between two areas in the auditory cortex of mustached bats"
 - Teng & Suga
 - o July, 2017
- Bats use frequency decomposition for all information
- Not all bats are blind



FFT

- Fast Fourier Transform
 - Spatial to Frequency 0
 - Measure of Intensity 0
 - Black & White 0
 - 0 255 н.
 - Red, Green, Blue (RGB) 0
 - R,G,B = 0-255
 - $I = \frac{1}{3}(R+G+B)$



$$F(x) = \sum_{n=0}^{N-1} f(n)e^{-j2\pi(x\frac{n}{N})} \qquad f(x) = \int_{-\infty}^{\infty} F(u)e^{j2\pi ux} du$$

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$$f(x) = \int_{-\infty}^{\infty} F(u)e^{j2\pi ux} du$$

$$F(x,y) = \sum_{m=0}^{M-1} \sum_{n=0}^{M-1} f(m,n) e^{-j2\pi(x\frac{m}{M}+y\frac{n}{N})}$$

$$f(m,n) = \frac{1}{MN} \sum_{m=0}^{M-1N-1} F(x,y) e^{j2\pi(x\frac{m}{M}+y\frac{n}{N})}$$

FFT









Gaussian Noise FFT



















The What Pathway



V1 simple cell edge detector



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• Gaussian Filter (GLPF)

$$D(u,v) = [(u - M/2)^{2} + (v - N/2)^{2}]^{1/2}$$

• Gaussian Low Pass Filter (GLPF)

$$H(u,v) = e^{-D^2(u,v)/2\sigma^2}$$

• Gaussian High Pass Filter (GLPF)

$$H(u,v) = 1 - e^{-D^2(u,v)/2D_0^2}$$







Differentiation & Pattern Formation



- A central problem in development: How do cells differentiate to fulfill different purposes?
- How do complex systems generate spatial & temporal structure?
- CAs are natural models of intercellular communication
- photos ©2000, S. Cazamine

Interaction Parameters



- R_1 and R_2 are the interaction ranges
- J_1 and J_2 are the interaction strengths

CA Activation/Inhibition Model

- Let states $s_i \in \{-1, +1\}$
- and *h* be a bias parameter
- and r_{ii} be the distance between cells *i* and *j*
- Then the state update rule is:

 $s_i(t+1) = \text{sign} | h + J_1 \sum s_j(t) + J_2 \sum s_j(t)$



$$D(u,v) = [(u - M/2)^{2} + (v - N/2)^{2}]^{1/2}$$

$$F(x,y) = \int_{m=0}^{M-1M-1} f(m,n) e^{-j2\pi(x} \frac{m}{M} + y\frac{n}{N})}$$

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M-1N-1

Image = Original - Transform







Conclusions

- Capsules? Yes, I agree.
- FFT?
 - Animal Camouflage mimics the difference in spatial frequency
 - The Effect of Bias creates a different appearance.
 - Does Camouflage correlate to the hunter?
 - Will two different species converge to the same "look" based on being hunted by the same animal?

Work Cited

https://medium.com/ai%C2%B3-theory-practice-business/understanding-hintons-capsule-networks-part-i-intuition-b4b559d1159b

https://medium.com/ai%C2%B3-theory-practice-business/understanding-hintons-capsule-networks-part-ii-how-capsules-work-153b6ad e9f66

https://www.frontiersin.org/articles/10.3389/fncom.2016.00092/full

https://web.eecs.utk.edu/~mclennan/Classes/420-527/handouts/Part%202B%20Patn%20Form.pdf

https://www.sciencedirect.com/science/article/pii/S0010027718300167 https://www-ncbi-nlm-nih-gov.proxy.lib.utk.edu:2050/pubmed/28456093

Work Cited Image

https://psychlopedia.wikispaces.com/mental+rotation

https://tex.stackexchange.com/questions/78145/how-can-i-draw-a-transparent-cube-in-3d-perspective

https://gizmodo.com/this-simple-sticker-can-trick-neural-networks-into-thin-1821735479

https://www.facebook.com/ThatManSloth/

http://www.qsimaging.com/ccd_noise_interpret_ffts.html

https://en.wikipedia.org/wiki/HSL_and_HSV