Computational roles of feedback signals

1. Fundamental computations in V1
2. Visual search
3. Pattern completion
Contributors (also known as “Good hombres”)

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Who is there? What is there? What are they doing?


Identification, Categorization, Generalization, Pattern completion, Inference, Learning.
Claim (without proof): over millions of years of evolution, “interesting” solutions to difficult problems have emerged through changes in neuronal circuits.
Some features of brain-based computations

- Hardware and software that work for many decades
- Parallel computation (with serial bottlenecks)
- Reprogrammable architecture
- Single-shot learning
- “Discover” structure in data
- Fault tolerance
- Robustness to sensory transformations
- Component interaction and integration of sensory modalities
Why study neural circuits?

• We can begin to explore high-level cognition at the neural circuit level
• Golden age for neural circuits: opportunity to manipulate, disrupt and interact with neural circuits at unprecedented resolution
• Theories can be rigorously tested at the neural level
• Empirical findings can be readily translated into algorithms
The visual system shows an approximately hierarchical architecture

Felleman and Van Essen 1991
First order approximation: “Immediate” recognition as a hierarchical feed-forward process

1. **Behavior**: We can recognize objects within ~150ms (e.g. Potter et al 1969, Thorpe et al 1996)

2. **Physiology**: Visually selective responses to complex shapes arise within ~150 ms (e.g. Keysers et al 2001, Hung et al 2005, Liu et al 2009)

3. **Computation**: Bottom up computational models perform relatively well in basic object recognition (e.g. Fukushima 1980, Riesenhuber and Poggio 1999)
Functional anatomy of the primate visual system


Hubel & Wiesel. *J. Physiol.* 1959

Kuffler, *J. Neurophys* 1953

Beyond immediate vision

Visual routines:
- Working memory, tasks, saccades, attention

Pre-frontal cortex

~150-500 ms

Learning, Memory (incl. spatial)

Medial temporal lobe

~250-500 ms

~100-150 ms

Anterior inferior temporal cortex

~40-50 ms

Primary visual cortex

~30-40 ms

Retina

~150-250 ms

Recognition (beyond initial fixation)
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Why are there so many feedback connections?

There are more horizontal + top-down projections than bottom-up ones (e.g. Douglas 2004, Callaway 2004)

What are feedback signals doing?
When?
Why?
How?

Markov et al 2012
Neurons in primary visual cortex show orientation tuning

Orientation selectivity

Gabor function

\[ D(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp \left[ -\frac{x^2}{2\sigma_x^2} - \frac{y^2}{2\sigma_y^2} \right] \cos(kx - \phi) \]

Hubel and Wiesel 1968
Hubel – Nobel Lecture
Reversible inactivation of V2/V3

JoJo Nassi and Richard Born
Feedback inactivation does not change orientation or direction selectivity

Nassi et al 2013, Gomez-Laberge et al 2014
Temporal dynamics of feedback inactivation effects

Nassi et al 2013, Gomez-Laberge et al 2014
Area summation curve in V1

$R_{\text{peak}}$

$R_{\text{asym}}$

Summation Field

Surround Diameter

Gomez-Laberge et al 2014
Feedback inactivation leads to reduced surround suppression

Gomez-Laberge et al 2014
A simple normalization model to explain area summation curves

\[ R_{ROG}(x) = R_0 + \frac{D(x)}{\sigma + N(x)} \]

\[ R_{ROG}(x) = R_0 + \frac{k_D [w_D \text{erf}(x/2w_D)^2]}{\sigma + k_N [w_N \text{erf}(x/2w_N)^2]} \]
Feedback increases the normalization width: $w_N$

- A: $0.04^\circ (p = 0.01)$
- B: $5 \text{ s}^{-1} (p = 0.06)$
- C: $7 \text{ s}^{-1} (p < 0.001)$
- D: $0.08 (p < 0.001)$

- E: $p = 0.7$
- F: $p = 0.2$
- G: $p = 0.8$
- H: $p = 0.006$

Gomez-Laberge et al 2014
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Feedback signals in visual search

Miconi et al, Cerebral Cortex 2016
The model can search for objects in cluttered images
The model’s performance is comparable to human performance in the same visual search task.
Consistency metrics

Miconi et al, Cerebral Cortex 2016
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3. Computations involved in v-s—l p-tt-rn c-pl-t-n
Inference and pattern completion as a hallmark of intelligence

A, C, E, G, I

1, 2, 3, 5, 7, 11, 13

V-s-a- R-c-g-i-i-n Visual Recognition Umbrella

Even though it was raining heavily, Jonathan decided to go out without an umbrella.

Also:
Other sensory modalities
Music
Social interactions
Objects can be recognized from partial information.
Behavior: Robustness to presentation of partial image information
Robustness to presentation of partial image information with occluded objects

See also Bregman 1981, Johnson and Olshausen 2005
Backward masking has been proposed to interrupt the effects of feedback/recurrent computations.

Models:

- For short delays (SOA<20ms), the mask reduces visibility of the first stimulus.
- For longer delays, the mask disrupts recurrent/top-down processing.

IT: Kovacs et al 1995, Rolls et al 1999
Backward masking disrupts pattern completion

A

500 ms  33-150 ms

RESPONSE

500 ms

A

B

C

Performance

Performance

Performance

Percent Visible

Percent Visible

SOA (ms)

n=21
Backward masking also disrupts recognition of occluded objects
We can interrogate neural circuits in the human brain
Example responses during object completion

Inferior Temporal Gyrus

Tang et al, Neuron 2014
Holistic responses (?)
The effect of masking correlates with neural delays in processing partial images.
Bottom-up models of object recognition

2000 “C2” units in the model
Model responses to 25 exemplar objects
Consider 20 units with high SNR (training data)
500 repetitions with different bubble locations
Train classifier with 70% of the repetitions
Test classifier on remaining 30% of the repetitions

Serre et al 2007

Krizhevsky et al, NIPS 2012
Bottom-up models significantly underperform in recognition of partial images

See also Pepik et al 2015, Wyatte et al 2012
But bottom-up models work well with minimal occlusion levels.

Supplement to Figure 4A in the main text extending the range of visibility to 100% (Fig. 4A showed 0 to 35% visibility). Note that reference 43 dealt only with 50-100% visibility (gray shaded area). The format and conventions are the same as in Fig. 4A. The black dotted line shows interpolated human performance between the psychophysics experimental values measured at 35% visibility and 100% visibility. Purely feed-forward models (e.g., fc7, pool5) match human performance for such high visibility conditions without the need for any recurrent computations.

See also Pepik et al 2015, Wyatte et al 2012.
2D object representation at the top of the model hierarchy is not robust to occlusion

Stochastic neighborhood embedding. Van der Maaten 2008
Difficulty for model correlates with neural delays
Hopfield network with binary neurons

Each neuron \( i \) has two states: \( V_i = 0 \) or \( V_i = 1 \)

Ensemble: \( \mathbf{V} = [V_1, V_2, ..., V_N] \)  
Note: \( \mathbf{V} = \mathbf{V}(t) \)

Synaptic strength: \( T_{ij} \)

If two neurons are not connected: \( T_{ij} = 0 \)

No self connections: \( T_{ii} = 0 \)

Update rule: \( V_i(t) = 1 \text{ iff } \sum_j T_{ij} V_j(t) > 0 \)

Hopfield, 1982
A recurrent network at the top may ameliorate the problem of missing information

\[ p = \text{prototypes (fixed)} \]
Adding recurrent connections at the top of the bottom-up models

\[ h_t = \text{ReLU}(W_h h_{t-1} + W_{6\rightarrow7}x) \]

\[ E = \sum_{i=1}^{i=p} \left[ \frac{1}{n} \sum_{j=1}^{j=n} (h_{4}[j] - \text{whole}h'[j])^2 \right] \]
Adding recurrent connections at the top of the bottom-up models

Note: RNNh has no free parameters dependent on the occluded objects!
No extrapolation across very dissimilar objects
Dynamics of recurrent computations
Image-by-image correlation between human and model performance
The model captures the effects of backward masking
1. Other cues (e.g. stereo, what is in front of what, context, world knowledge)
   a. Stereo cues, what is in front of what
   b. Context
   c. World knowledge (people sit on chairs, things fall if there is no support, kitchens may have coffee makers but not giraffes)

2. How to integrate information across space and time to understand a scene
   a. Integrating fovea and periphery
   b. Integrating information across saccades

3. The role of memory
   a. To compare sensory inputs to stored representations
   b. Working memory
Context example 1
Context example 4
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