WEEK 2: SHUNTING COMPETITIVE NETWORKS, CONTRAST SENSITIVITY AND CONNECTIONS BETWEEN PSYCHOPHYSICS, ELECTROPHYSIOLOGY, AND MODELING

1) Shift property and Weber law
2) Retinal physiology
3) Hyperpolarization and featural noise suppression
4) Distance-dependent shunting networks
5) Another approach (Marr)
6) Back to the recurrent network
7) A tour to the three worlds of neuroscience

THE PLAN

In the last class you realized that certain mathematical formulation which describes the dynamic of a network can model certain classic phenomenon (e.g. normalization).

Today, we follow the same trend, plus we will have a tour to three apparently different approaches, namely: Psychophysics, electrophysiology, and modeling

VISUAL ADAPTATION TO INPUT LEVEL

In “early” vision, two main types of adaptation occur:

1) Bleaching: Breaking down of pigment in photoreceptors due to exposure to light
2) Background: modulation of response to a small area when the input level in its surround is varied

Although bleaching effects are large, they do not account for all perceptual effects.

We are concerned with background adaptation.

What in general is “adaptation”?

Is it “habituation”? Learning? Weight changes in a network (cf. “adaptive filter”)?

The human visual system’s operating range spans 15 orders of magnitude!
THE SHIFT PROPERTY, I

An increase of total background input energy to the network creates a strictly horizontal displacement of response curves. There is no loss of sensitivity, in the sense that nodes still employ their entire output range. (What about input range?)

As opposed to, for example:

Here “too much” inhibition from background reduces dynamic range of output. (This pattern is characteristic of “subtractive” inhibition).

THE SHIFT PROPERTY, II

More specifically, since \( x = \sum_{k \neq i} x_k = \frac{BI}{A+I} = \frac{BI}{A+I + \sum_{k \neq i} I_k} \)

consider one input, \( M = \log_e(I_i) \), and its background \( L = \sum_{k \neq i} I_k \)

Then \( x_i(M, L) = \frac{Be^M}{A + e^M + L} \)

\[ x_i(M_0, L_1) \]

\[ \log \text{input} \quad M_0 + S \quad M_0 \quad (\log \text{input}) \]

\[ L_2 > L_1 \quad \text{so} \quad S < 0 \]

SHIFT PROPERTY: There exists an \( S \) such that:

\[ \forall M : x_i(M + S, L_1) = x_i(M, L_2) \quad S = \log_e \left( \frac{A + L_1}{A + L_2} \right) \]

EXAMPLES OF SHIFT PROPERTY

Note that for two sequences of background increments, shifts get progressively smaller for linear increases in background levels.

SUPPLEMENTARY MATERIAL FOLLOWS IN FOUR PANELS

Note: The next four panels contain material from ancient manuscripts recently discovered in the ruins of what is believed to have been a monastery of a zealous neural modeling sect on the site of what is presently the BU Math Department.

They contain some algebraic derivations. While I will not “lecture” on these panels, and while you will not be expected to produce these derivations on the midterm exam, “what could it hurt, to study them”?

Note: The next four panels contain material from ancient manuscripts recently discovered in the ruins of what is believed to have been a monastery of a zealous neural modeling sect on the site of what is presently the BU Math Department.
**DERIVATION OF SHIFT PROPERTY**

Find $S$ such that

\[
\frac{B e^{M+S} + L_1}{A + e^{M+S} + L_1} = \frac{B e^{M} + L_1}{A + e^{M} + L_1}
\]

\[
e^S (A + e^M + L_1) = A + e^M e^S + L_1
\]

\[
e^S (A + L_1) = A + L_1
\]

\[
e^S = \frac{A + L_1}{A + L_2}
\]

\[
S = \log_e \left( \frac{A + L_1}{A + L_2} \right)
\]

Note that value of $S$ is independent of $M = \log_e I_i$.

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**DERIVATION OF SHIFT SIZES**

Shifts get *smaller* as background intensity increases (for *linear* increases in $L$).

Let $L_n = nL$ where $L = \sum_k I_k$

That is, let background intensity increase.

\[
S = \log_e \left( \frac{A + (n+1)L}{A + nL} \right)
\]

\[
= \log_e \left( \frac{A}{A + nL} + \frac{(n+1)L}{A + nL} \right)
\]

As $n \to \infty$, $S \to \log_e \left( \frac{1}{L} \right) = 0$.

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**DERIVATION OF WEBER LAW PROPERTY. I**

Derivation of "Weber law" (Grossberg, 1983) Section 2.3

\[
\frac{dx_i}{dt} = -AX_i + (B - x_i)I_i - x_i \sum_j I_j
\]

Let $I_i = K + \Delta I$

\[
I_i = K, \text{ for } j \neq i \quad \text{before increment}
\]

Then:

\[
x_i = B \frac{(I + \Delta I)}{A + I + \Delta I} \left( \frac{K + \Delta I}{nK + \Delta I} \right)
\]

If $I >> \Delta I$ and $n >> 1$, $x_i = B$.

\[
k + \Delta I = \frac{I + \Delta I}{nK + \Delta I}
\]

\[
\frac{nK + \Delta I}{I + \Delta I}\n
a constant

---

**DERIVATION OF WEBER LAW PROPERTY, II**

If $I >> A$

\[
B \frac{(I + \Delta I)}{A + I + \Delta I} \approx B
\]

\[
\frac{B (I + \Delta I)}{A + I + \Delta I} \approx B
\]

So

\[
x_i \approx B \left( \frac{\Delta I}{I} + D \right)
\]

If $x_i$ is detectable when it exceeds some threshold $\Gamma$,

\[
\Gamma \approx B \left( \frac{\Delta I}{I} + D \right)
\]

\[
\sum_r \frac{R}{B - D} \approx \frac{\Delta I}{I}
\]
**WEBER LAW**

*Definition:* The smallest increment, $\Delta I$, in some sensory stimulus (not necessarily visual) that can be reliably detected* relative to some background level, $I$, is called the “just noticeable difference” (JND) for that background.

**Weber Law:** Over a wide range of some sensory dimension, the ratio of a JND for a background to that background is a constant; i.e.,

$$\frac{\Delta I}{I} = C$$

*Important methodological issues concerning criteria for determining that some stimulus can be “reliably detected” will be discussed at a later time.

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**FECHNER’S LAW**

Quoting from a recent posting to CVNet:


“As many of you are aware, October 22, 1850 is considered an important day in the history of psychology and sensory science. On that morning, Gustav Fechner formulated his famous quantitative relation between mental sensation and physical stimulus. Fechner’s law is $S = K \log I$ (the mental sensation varies as the logarithm of the material stimulus).”

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**FECHNER’S LAW AND LOGARITHMIC PROCESSING**

Fechner and Weber formulas are related, if you assume that all JNDs are equal increments in sensation.

---

**TRANSLATING GROSSBERGSE TO ENGLISH, PART 1 OF N**

G ‘83 states that . . .

while the shift property occurs in logarithmic coordinates, it is not due to logarithmic processing.

Translation:

There is no stage in network computations that performs an operation called: “Take the log of your input.”

Remark:

This is not an empty distinction, as there are many computational models that do have such a stage.
**SUBTRACTIVE INHIBITION**

Grossberg's “target” is (at times!) the *subtractive* (additive) modeling of “lateral inhibition” (Ratliff, 1965; Cornsweet, 1970.)

Put in a form closest to that of Grossberg’s UMAP equation:

\[
\frac{dx_i}{dt} = -Ax_i + BI_i - \sum_{k} I_k
\]

At equilibrium:

\[
x_i = \frac{BI_i - \sum_{k} I_k}{A}
\]

Note: Unlike the case for the shunting network considered so far, inhibition can drive a node of *this* network below zero.

Having a node potential in a “computational” neural network go below zero is sometimes called “hyperpolarization,” by analogy to a neuron *in vivo* being driven away from its resting level and further away from depolarization by some inhibitory input.

Note that in most “computational” or “artificial” neural modeling studies, a convention is employed whereby high cell activity is coded by positive numbers, and numbers below zero are assumed not to result in cell outputs -- notwithstanding the failure of direct analogy of such values to those of real neurons.

Note: Equations that are hybrids of those containing shunting and (input-dependent) subtractive inhibition are possible, as we will soon see.

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**BIOLOGICAL NETWORKS: RETINAL PROCESSING**

Werblin’s (1970) study of mudpuppy retina:

- **Receptors**
- **Horizontal cells**
- **Bipolar cells**

*intracellular* electrode (records “graded” potentials)

**Q:** Do bipolars spike?

**Findings:**
1) *Center-surround* processing
2) *Weber law* in intermediate input range
3) *No hyperpolarization* from surround*
4) *Shift property*

* Suggests *shunting* inhibition. Why?

**WERBLIN (1970) DATA**

Above: Responses to light increments by a single ganglion cell as background is raised by two log units.

Shift is “imperfect,” with some loss of dynamic range.

**Ganglion cell threshold**

**Receptor**

**Horizontal cells**

**Bipolar cells**

**Luminance level shift**

**Amacrine and ganglion cells**
ASIDE: HUMAN RETINAL PATHWAYS (1 OF 3)

Reading physio figures:

How is time indicated?

How is cell potential (or firing rate) indicated?

Read these diagrams with "computational" questions in mind. E.g., why have separate ON and OFF pathways?

Note: this edition makes no mention of possible “cross-talk” between ON and OFF channels in the retina.

ASIDE: ON/OFF CROSSTALK? (2 OF 3)

In 1991 CNS student (and, subsequently, CNS Professor) Paolo Gaudiano predicted on theoretical grounds that there should be convergent input from ON and OFF bipolar cells onto each of ON and OFF ganglion cells.

This was a genuine “prediction;” i.e., the kind that points forward in time.

ASIDE: NOW YOU SEE IT; NOW YOU DON’T (3 OF 3)

Compare the figure shown two panels ago with the corresponding one from the 3rd edition of K, S, & J:

What gives?

a) Crosstalk does not exist after all?

b) K, S, & J has been “dumbed down”?

c) Neither of the above?

ELABORATIONS OF SHUNTING NETWORK: HYPERPOLARIZATION

Hyperpolarization and, more generally, the effects of subtractive inhibition, can occur in a so-called “shunting” network, provided that the passive (“resting”) potential, $V^P$, is different from $V^-$, the potential that is farthest from generating a node’s output,

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)I_i - (x_i + C)\sum_{k \neq i} I_k$$
HODGKIN/HUXLEY EQUATIONS AND SHUNTING NETWORKS

Membrane equations of physiology
(Hodgkin and Huxley, 1952; Carpenter, 1981)
of the following (simplified) form

\[ C \frac{\partial V}{\partial t} = (V^+ - V)g^+ + (V^- - V)g^- + (V^0 - V)g^0 \]

excitatory inhibitory passive
Na\(^+\) channel K\(^+\) channel Cl\(^-\) channel

\[ V^+ \rightarrow B \]
\[ C \rightarrow 1 \]
\[ V^- \rightarrow D \]
\[ V^0 \rightarrow 0 \]
\[ g^+ \rightarrow A \]
\[ g^- \rightarrow \sum I_k \]

inspired the simple
shunting network equation:

\[ \frac{dx_i}{dt} = -Ax_i + (B - x_i)I_i - (x_i + C)\sum I_k \]

HYPERPOLARIZATION AND “ADAPTATION LEVEL”

For hyperpolarizing network equation

\[ \frac{dx_i}{dt} = -Ax_i + (B - x_i)I_i - (x_i + C)\sum I_k \]

with \( C > 0 \),
at equilibrium:

\[ x_i = \frac{(B+C)I}{A+I} \left( \theta_i - \frac{C}{B+C} \right) \]

\( G \) refers to \( \frac{C}{B+C} \) as the “adaptation level” that must
be exceeded by \( \theta_i \) in order to trigger a positive response
for node \( x_i \).

\[ \begin{array}{c}
\text{Note: In vivo, generally } B \gg C, \text{ so } \frac{C}{B+C} \ll 1 \\
\end{array} \]

That is, the range between saturation level and resting
level (“zero”) is generally greater than the range between
resting level and maximum hyperpolarization level.

HYPERPOLARIZATION AND THE SHIFT PROPERTY

The presence of a hyperpolarizing term

can cause curves
to deviate from being parallel.

Note: Weird parameters
are chosen here to
accentuate the effect.

Note: Shift decreases at
larger values of \( M \) (not of \( L \)).

G: “SYMMETRY-BREAKING MECHANISM”

DYNAMICS (typical):
The positive (output producing) range is extended (amplified). The negative (hyperpolarized) range is compressed.

For non-distance dependent network with hyperpolarization:

\[ \begin{array}{c}
\text{extended} \\
\text{compressed} \\
\end{array} \]

\[ \frac{B}{C} = \frac{(n-1)}{1} \text{ for “perfect” balance.} \]

i.e. an input has to be greater than \( 1/n \) in order for output to be positive.

GEOMETRY (typical):
The spatial range of sensitivity to excitatory signals is narrower. The spatial range of sensitivity to inhibitory signals is broader.
FEATURAL NOISE SUPPRESSION*
A network with hyperpolarization can have parameters set so as to attenuate uniform regions of a pattern, which contain no information. (“Just a DC shift.”)

\[ I_i \rightarrow x_i \]

Recall, for simple network:

\[ x_i = \frac{(B + C)I}{A + I} \left( \theta_i - \frac{C}{B + C} \right) \]

Result: Uniform pattern is suppressed independent of intensity of \( I_i \).

Try: \( B = (n - 1)C \)

\[ \frac{C}{B + C} = \frac{1}{n} = \theta_i \]

\( x_i = 0 \)

* G jargon alert!

NEED FOR DISTANCE-DEPENDENT INTERACTIONS

To get the benefits of “featural noise suppression” for parts of a pattern, interactions among network nodes must not be uniform across the whole network, as for the equations considered so far, whose “network anatomies” are:

Consider a network anatomy such as:

Here one can meaningfully speak of “center-surround” processing, and perform featural noise suppression for uniform regions of a globally nonuniform pattern (a.k.a. “edge enhancement.”)

* Jargon alert: See next panel.

NOTE: “Center-surround” is a misnomer for the anatomy of the previous panel, as there are no neighborhood relations or, equivalently for our purposes, distance measures – as embodied in connection weights -- among nodes. Thus, no node can be in the “center” of particular others.
G’s use of the phrase “multi-channel” for distance-dependent (localized) spatial interactions in a network is not the same as what most of the vision world calls “multiple channels” of spatial frequency tuning. In place of the latter concept, Grossberg typically refers to “multiple scales” -- although multiple scales are not viewed as being sensitive to spatial frequency as such, but to a complex of attributes, including spatial frequency.

**SHUNTING NETWORK* WITH DISTANCE-DEPENDENT TERMS**

\[
\frac{dx_j}{dt} = -Ax_i + (B - x_i) \sum_{k=1}^{n} I_k C_{ki} - (x_i + D_i) \sum_{k=1}^{n} I_k E_{ki}
\]

\[
C_{ki} = C \exp\left(-\mu(k-i)^2\right)
\]

\[
E_{ki} = E \exp\left(-\nu(k-i)^2\right)
\]

Example:

\[
C_{ki} = \begin{cases} 
4 & \text{if } k=i \\
1 & \text{if } |k-i| = 1 \\
0 & \text{otherwise}
\end{cases}
\]

apart from “outer boundary effects”

\[
\begin{array}{cccccccc}
I_k & 3 & 2 & 5 & 6 & 6 & 6 & 5 \\
k & 1 & 2 & 3 & 4 & 5 & 6 & 7 \\
\end{array}
\]

* Note: This network has both subtractive and shunting inhibitory terms.

**EQUILIBRIUM OF DISTANCE-DEPENDENT NETWORK**

Set \( \frac{dx_j}{dt} = 0 \) and recall that \( I_k = I \theta_k \)

\[
x_i = \frac{1}{A + I \sum_{k=1}^{n} \theta_k (BC_{ki} - DE_{ki})} \sum_{k=1}^{n} \theta_k (C_{ki} + E_{ki})
\]

**Result:**

\[
\text{Numerator: DOG (difference of Gaussians)}
\]

\[
\text{Denominator: weighted SOG (sum of Gaussians)}
\]

\[
\text{scaled against constant, } A
\]

**Hot tip:**

See Neumann, H. (1996), *Neural Networks, 9*(6), 921-936. (Suppl. Reading, Week 3) for analysis of this equation.
DISTANCE-DEPENDENT FAQS

$$x_i = \frac{I \sum_{k=1}^{n \theta_k (BC_{ki} - DE_{ki})}}{A + I \sum_{k=1}^{n \theta_k (C_{ki} + E_{ki})}}$$

$$C_{ki} = C \exp[-\mu(k-i)^2]$$

$$E_{ki} = E \exp[-\nu(k-i)^2]$$

Should $$C = \frac{1}{\sigma \sqrt{2\pi}}$$? Should $$\mu = \frac{1}{2\sigma^2}$$?

How do I choose the other constants?

How broad should “center” and “surround” be?

Notes: Rectification of output is generally assumed.

$$x_i$$ is sensitive to (Grossbergian) reflectances (ratios) in regions of rapid changes of input level*.

“Gradual” changes -- relative to B, D, \(\mu, \nu\) -- are discounted.

Compare last two points to discussion of Retinex, brightness constancy, etc. in Lecture 1.

*Yes, but, WHAT about the pattern of $$x_i$$’s demonstrates that sensitivity?

FEATURAL NOISE SUPPRESSION

Recall: “Featural noise suppression” is G’s phrase for producing zero output for homogeneous regions of input.

Theoretically, this occurs for distance-dependent equation iff:

$$B \sum_{k=1}^{n C_{ki}} \leq D \sum_{k=1}^{n E_{ki}}$$

In practice, you must pay attention to truncation effects when coding discrete approximations of Gaussians.

To get a numerical zero output (after rectification) at a given node, it may be necessary for the input pattern to be homogeneous over as many network locations as the size of the discrete inhibitory kernel.

MENTAL CONVOLUTION

How would filters or detectors like these:

Respond to patterns like these?
A distance-dependent network cannot possibly compute Grossbergian reflectances, which are defined over the set of all inputs.

Reflectance here depends on input strength there.

*feature or bug?*

Instead, compute ratios of local “reflectances”, weighted by network parameters.

In a recent edition of CN530, the slide on the previous panel generated considerable controversy, because the authors had apparently “post-processed” the output of the shunting network through a sigmoidal output function!

Could equivalent results be achieved without such a “boost”?

Consider this figure from Waxman et al., (1997), *Neural Networks*, 10(1), 1-6:

Quoting from caption of Figure 1:
“(a) High-end of 12-bit dynamic range; (b) low-end of 12-bit dynamic range; (c) entire 8-bit dynamic range after center-surround shunting neural processing of original 12-bit imagery. All objects are clearly visible without saturation at either end of the compressed dynamic range.”

“BIOLOGICAL PLAUSIBILITY” OF SHUNTING IN CORTEX*


...looked for conductance changes as evidence for shunting, (with respect to directional selectivity)

*Conclusion:* Shunting inhibition is too small to measure.


...looked for linearity of synaptic summation

*Conclusion:* Synaptic summation is linear-- ergo no shunting.

Subsequent papers rule out shunting on dendritic spines and other loopholes.

Note that “shunting networks” are only incompatible with this data in an extreme parameter range -- i.e. when $D=0$, the shunting network is shunting (only); nonzero $D$ values admit subtractive (nonshunting) inhibition.

* Thanks to David Somers for info in this and next three panels.
POINTS TO PONDER, CIRCA 1998

1. Until 1998, it appeared that shunting inhibition was not performed by cortical neurons. This is, perhaps, still believed by many experimentalists and biases them against “shunting” models.

2. To a physiologist, “shunting inhibition” is purely silent, meaning that if you stimulate an inhibitory fiber alone, no hyperpolarization of post-synaptic cells will occur. Biophysically this means that the reversal potential of inhibition is at the resting potential (or $D = 0$) and, more importantly, that large conductance changes occur. The large conductance changes have a divisive or normalizing effect on excitatory current. Typical, real conductance changes are thought to be on the order of 20-30%. “Heeger’s” Normalization Model (i.e., a shunting network) requires 400% conductance changes to achieve normalization and hence did not appear to be “plausible.”

3. Conductance change is equivalent to the change in the size of the denominator of the equilibrium solution of the shunting equation. So, the data appear to rule out significant inhibitory normalization via the denominator (even if $D$ is not exactly zero).

4. Something like normalization clearly occurs in cortex, but at a slower time scale than spiking (seconds, rather than milliseconds).

CORTICAL SHUNTING REDUX!

But wait! Just when cortical shunting appeared at death’s door, Judith Hirsch (Rockefeller) and Lyle Borg-Graham (France) have independently reported measuring conductance changes on the order of 200 – 300% at recent conferences!

See:


For further info and updates on cortical shunting, contact David Somers (CNS alumnus, B.U. Psychology professor, smart guy, and all-around swell person) at: somers@bu.edu.

LEADING CANDIDATE MECHANISMS FOR CORTICAL NORMALIZATION (STILL CIRCA 1998)

1) synaptic depression at active synapses
2) metabotropic (non-ionotropic) glutamate receptors
3) intrinsic modulation (normalization) of synaptic currents.

It is also possible that the network is very clever and somehow balances hyperpolarizing (non-shunting) inhibition with excitation.

Bottom lines:
1) Normalization is important, and does occur in cortex.
2) “Shunting network model” has simple and intuitive way of achieving normalization.
3)Apparently, something other than shunting as such may be performing normalization in cortex (on a relatively slow time scale.)

CONTRAST SENSITIVITY

1) Marr and Grossberg:
   - Symbols, patterns, and the principle of least commitment
   - Marr’s “zero-crossings” vs. network dynamics

2) Recurrent networks
BACKGROUND

Many formalisms have been applied to “explain” early vision. Many kinds of psychophysical experiments have been run. Much physiological data has been collected.

Yet . . . vision researchers do not have a consensus about how to characterize early and middle* vision.

* “before**” recognition of objects, but including detection of complex features (e.g. “T-junctions”) and perceptual organization

** Why does this word have “shudder quotes” around it?

ALTERNATIVES TO NETWORK MODELS

Near consensus: Adaptation, contrast sensitivity, normalization, filtering, etc.

Far from consensus: Receptive field dynamics, parallel channels (including magno/parvo, ON/OFF, what/where, etc.), and more . . .

Where to start?

Comparison of network approach to the two dominant modeling traditions of recent decades:

Marr’s computational approach
(Quasi-)linear systems approach

MARR’S ZERO-CROSSINGS

Marr (1980) recommends that image edges be detected by computing the zero-crossings of

\[ \nabla^2 G \ast I \]

the Laplacian of a Gaussian filtering of the image data.

Many, if not most, of the papers that present “computational” models in vision today cannot be easily classified as any of “network,” “Marr,” or “linear systems” in style.

Nonetheless, aspects of these approaches form useful dimensions for evaluating the explanatory power of models. Accordingly, we will study them in CN530 both for historical context and as guides to thinking about more complex or hybridized modeling efforts.
Marr also points out that
\[ \nabla^2 G * I \]
can be well-approximated by a DOG, if the ratio of excitatory to inhibitory space constants is about 1:1.6.

**DEFINITION OF CONTRAST**

\[ C = \frac{P - T}{P + T} \]

The “Michaelson contrast” formula is one of several equivalent forms of the same idea.

E.g., one might instead choose an expression in which the mean of two luminances was in the denominator.

Do not confuse the word “contrast” in phrases like “Michaelson contrast” or “stimulus contrast” or “image contrast” with its usage in phrases like “brightness contrast” or “color contrast.”

The former usages refer to characteristics of a visual stimulus that can be objectively measured (e.g., with a photometer.)

The latter usually refer to perceptual phenomena.
ZERO-CROSSINGS AGAIN

Zero-crossings have no height no width.

They are (just) spatial loci. (They offer a compact symbolic code of the coordinate values for a location containing an edge.)

Note: Marr and Grossberg do not disagree on the facts.

DAZZLING (FOR ITS TIME) DEMO

Figure 2-15. Another example of zero-crossings; here, the intensity of the lines has been made to vary with the slope of the zero-crossing, so that it is easier to see which lines correspond to the greater contrast. (Courtesy BBC Horizon.) [From Marr, 1982; emphasis added.]

MODULARITY OF MARR’S APPROACH

Huertas & Medioni, 1986 IEEE PAMI, 8(5), 651.

Use slope at zero-crossings of various sized operators (σ) to compute contrast.

Slope, or peak-to-peak amplitude, or area . . .

Note: While measures of contrast can be gotten, they are represented separately from the code for the zero-crossing itself.

SYMBOLIC AND NONSYMBOLIC PROCESSING

Marr’s primal sketch is composed of “primitives” such as:

<table>
<thead>
<tr>
<th>BLOB</th>
<th>EDGE</th>
<th>BAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>(POSITION 146 21)</td>
<td>(POSITION 184 23)</td>
<td>(POSITION 118 34)</td>
</tr>
<tr>
<td>(ORIENTATION 105)</td>
<td>(ORIENTATION 128)</td>
<td>(ORIENTATION 128)</td>
</tr>
<tr>
<td>(CONTRAST 76)</td>
<td>(CONTRAST -25)</td>
<td>(CONTRAST -25)</td>
</tr>
<tr>
<td>(LENGTH 16)</td>
<td>(LENGTH 25)</td>
<td>(LENGTH 25)</td>
</tr>
<tr>
<td>(WIDTH 6)</td>
<td>(WIDTH 4)</td>
<td>(WIDTH 6)</td>
</tr>
</tbody>
</table>

What in the image would cause the following kinds of outputs of $\nabla^2 G * I$?

same height: vs

same width vs

Marr uses symbolic tokens of place, size, and featural qualities.

Compare with: “gestalts,” or equilibria (or other characteristics) of complex, nonlinear dynamical systems.
**EXPLICIT VS IMPLICIT REPRESENTATION**

Re: Marr's Chapter 2
What are the advantages and disadvantages of *explicit* vs. *implicit* representation of information?

Consider: “Spatial coincidence assumption” (page 70) for zero-crossings at multiple spatial scales, whereby zero-crossings that are spatially coincident for many spatial scales (degree of blur) are taken as more likely to correspond to “true” discontinuities in the world than those occurring at few scales.

Is this the reason for having “multiple spatial frequency channels” in human vision?

Is postulation of “virtual lines” as primitives a good idea?

What is a primitive?

What is the difference between an axiom and a postulate?

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**MARR’S COMPUTATIONAL THEORY**

Six properties of images for which differences within the image are taken as evidence for differences in the layout of surfaces in the world:

- Brightness
- Size (length, width)
- Orientation
- Density
- Distance apart
- Orientation structure

Properties of tokens

Properties of variation among tokens

Note: Marr’s emphasis is on perceiving surface layout. (rather than accounting for surface appearance.)

Cf. Gibson, 1966:
The senses considered as perceptual systems.

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**LEVELS OF ANALYSIS: FIRST LAW, OR LAST STRAW?**

**Computational theory**
**Representation and algorithm**
**Implementation**

Marr's proposal has appeal, because . . .

Does Marr follow his own prescription?

**Critiques:**
- Underconstrained (cf. serial/parallel)
- Misses key design issues
- Produces “brittle” modules

**Representational issue:**
- What is a symbol?
- Why (when, how) would living matter be able to “behave symbolically”??
FEEDBACK SHUNTING NETWORKS

“recurrent network”,
“reverberating network”
“competitive network (with feedback)”

Given a network’s anatomy (connectivity), it signal functions, parameter restrictions, and initial conditions, ask:

STABILITY: Is there storage of a (nontrivial) pattern?

PATTERN TRANSFORMATION: What happens to initial activity pattern? Is it preserved, destroyed, smoothed, contrast-enhanced, …?

Method:
- Initialize network
- Shut off inputs
- Study “reverberations”

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PROPERTIES OF RECURRENT COMPETITIVE NETWORKS

Grossberg, 1973: (Chapter 8, _Studies of mind and brain_)
What happens to $X$ (total network activity) as (time) $t \to \infty$?}

_Possibilities:_

- $X \to 0$ “collapse” of all activity
- $X \to \infty$
- $X \to$ constant
- $X \to$ one of finitely many values
- $X \to$ one of infinitely many (finite) values
- $X$ oscillates
- $X$ is chaotic (not in 1973!)

Key result:

_Network anatomies (patterns of connections) and signal functions constrain outcomes._

Q: Why this?! Why now?!
A: To see what other kinds of representations (besides zero-crossings, etc.) are even possible!

PATTERN VARIABLES

Definition of pattern variables (functions of time): $X_i = \frac{X_i}{X}$ (compare with G’s definition of “reflectance”)

What happens to _initial_ $X_i$’s as $t \to \infty$?

_Possibilities:_

- Each $X_i \to X_i$ _nothing_ happens; i.e. “perfect storage”
- Maximum $X_i \to I$ “winner take all” (a.k.a. “choice”)
- All $X_i$’s $\to I/n$ “uniformizing” where $n =$ number of nodes in network
- Some $X_i$’s $\to 0$ “quenching threshold” yields contrast enhancement of activity of surviving nodes

ON-CENTER, OFF-SURROUND RECEPTIVE FIELDS

Grossberg’s (1973) Figure 5 looks like this

and is labeled “recurrent on-center, off-surround network.”

_The phrase “on-center, off-surround” has historically referred to the “receptive fields” of neurons, viewed functionally._

The relation of a neuron’s connectivity with other neurons [ANATOMY] to that neuron’s receptive field [PHYSIOLOGY] is tricky.
MODELERS AND PHYSIOLOGISTS: “DIVIDED BY A COMMON LANGUAGE”

**RECEPTIVE FIELD** -- functional
Where **on the retina** will stimulation yield a response at this (cortical) cell?

**KERNEL** -- structural
Which network cells send inputs directly to this cell?

Kernels are trivial for a modeler to specify, but are generally **not observable** for a physiologist!

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RECURRENT, DISTANCE-DEPENDENT NETWORKS

Sketch of connectivity of recurrent generalization of distance-dependent shunting network with Gaussian kernels:

While we will refer to many such networks later in the course, consider next Grossberg’s 1973 analysis of recurrent networks **without** distance-dependent kernels. (Why?)

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Note: Equation (12) of Grossberg (1973) means (only) what it says regarding feedback. I.e., positive feedback goes only from a given \( v_i \) to itself. The analysis is for a network whose connections are *not* distance-dependent.

\[
\frac{dx_i}{dt} = -Ax_i + (B - x_i)\left[ f(x_i) + K_i^+ \right] - x_i \sum_{k \neq i} f(x_k) + K_i^-
\]

Let inputs \( K_i^+, K_i^- \) be “on” (i.e., positive in value) during some time interval, [-\( T \),0].

This generates an *initial pattern* of activities, \( x_i(0), i = 1, 2, \ldots n \).

Study “reverberations,” \( \lim_{t \to \infty} x_i \) with inputs shut off.

\[
\frac{dx_i}{dt} = -Ax_i - f(x_i)
\]

Equation (12) of Grossberg (1973)

RESULT: The “shape” of \( f \) makes all the difference concerning the destiny of *pattern variables* and *total network energy*. 
Connections between Psychophysics, Electrophysiology, and Modeling

1. Can a psychophysics experiment suggest an electrophysiology test?

2. Can psychophysics suggest a modeling idea?

3. When are the electrophysiology results incorporated into the modeling ideas?

4. How can modeling ideas give a better view of electrophysiological results?
A Psychophysics Observation
Kanizsa (1979)

Example 1: A triangle occluding three circles
Example 2: A grouping across scenic positions not receiving contrastive input

Oriented receptive fields have a limited spatial range

Oriented receptive fields

Psychophysics Experiments
Electrophysiology Experiments

Psychophysics Experiments
Electrophysiology Experiments?

There are cells in V2 that respond to illusory contours when their receptive fields are just on the illusory part

When inducers are offset the response disappears

Illusory contours and Electrophysiology
von der Heydt (1984)

Corresponding Modeling Idea
Cohen and Grossberg (1984)
Grossberg and Mingolla (1985)

The old model of bipole has two lobes.
Both lobes have to have excitatory inputs for bipole activity.
Result: Interpolation, Yes
Extrapolation, No

Modeling Idea

Psychophysics Experiments
Electrophysiology Experiments
Laminar Organization of Cerebral Cortex

In vitro preparation of layer 2/3 of Ferret visual cortex.

Caveat: Layer 2/3 is in isolation, getting sound inference needs more care.

Initial positive area of activity is followed by the expanding ring of suppression.

The panels are shown in sequence to give you a better impression of excitation and inhibition dynamics.

Another activity spread after stimulation.
Resultant Grouping

Boundary representation that emerges from long range excitation and short range inhibition

Contribution to Modeling Idea

Electrophysiology Experiments

Modeling Idea


Clusters of long range positive connections accompanied by short range inhibitory interneurons

Contribution to Modeling Ideas

Electrophysiology Experiments

Modeling Idea


Does it remind you older modeling idea?

Emergent Older Modeling Idea

Grossberg and Raizada, 2000

The following model of bipole grouping cells emerged from the psychophysical property (interpolation, yes, extrapolation, no) + Following electrophysiological data

2/3 pyramidal cells to 2/3 pyramidal cells
Bosking et al. (1997, shrew), Schmidt et al. (1997, cat)
2/3 pyramidal cells to 2/3 inhibitory interneurons
2/3 inhibitory interneurons to 2/3 inhibitory interneurons
Tamas et al. (1998, cat)

Compare this circuit with the previous panel circuit. What are differences? At which level this difference may generate discrepancy?
Aperture Problem

What is the difference between the direction of movement inside the aperture and outside it? This may cause trouble!

Aperture Problem: Any local motion detector can measure only the component of motion perpendicular to a contour that extends beyond its field of view.

It is especially true for small V1 receptive fields: 0.2 – 0.5 degree of visual angle. MT receptive field size are around 3-5 times larger than V1 cells at the same eccentricity.

Experiment Design

The length of each bar was always 3 degree, significantly longer than corresponding receptive fields in V1, but smaller than the excitatory receptive parafoveal and peripheral MT.

This is such to encourage the even excitation by endpoints.

Direction Tuning Polar Curve

Average activity of the cell at each direction is plotted in a polar coordinate and connecting them by straight lines.
Resolving the aperture problem takes time:

Earlier

Later

MT cell has a ~150 ms time delay to resolve aperture problem, but it can solve it finally.

Seeing MT Cells!
Lorenceau J., et al., 1993

From Electrophysiology to Psychophysics
We can see our MT cells: Again psychophysics!

The tilted bar moves horizontally back and forth, but we illusively observe a temporary upward/downward movement of the middle point that turns to real direction.
Close the Loop by Modeling

Remember the inward illusory contour mechanism:

Psychophysics Experiments

Modeling Idea

Electrophysiology Experiments

One idea could be that the detection delay of the real direction is due to the same inward mechanism from line ends to the middle (?) Grossberg and Mingolla (1993)

da Vinci and Classic Stereopsis

In (a,1), occlusion configuration blocks the view of the object, therefore stereogram (a,2) can reproduce the viewing condition.
In (b,1), both eyes see the farther object with their line of sight having different distance from the nearer object edge.

Anatomy: Regions with Different Eye of Origin

Anatomical Data

Psychophysics Problem

Many primary visual cortex cells still input from one eye

da Vinci Stereopsis

da Vinci stereopsis, relies on the eye of origin, therefore, originates in V1
Shimojo and Nakayama (1990)

Psychophysics Problem

Anatomical Data

da Vinci (a)

Classic (b)

Uncrossed-fusers
**Classic Stereopsis**

Classic stereopsis, relies on the eye of origin too, therefore originates in V1

**Uncrossed-fusers**

Psychophysics Problem  Anatomical Data  Electrophysiology Data

There are obligate cells in V1

Poggio (1991)

**Open Question for Modelers**

Grossberg and Howe (2003)

Complex Cells  Simple Cells

2/3A  V1  3B

4

L eye  R eye

Inhibitory cells

Psychophysics Problem  Anatomical Data  Electrophysiology Data  Modeling Idea