WEEK 3: CONTRAST SENSITIVITY, LINEAR SYSTEMS APPROACH, AND SPATIAL SCALES

1) Marr and Grossberg: Symbols, patterns, and the principle of least commitment  
   a) Marr’s “zero-crossings” vs. network dynamics  
   b) Marr’s levels of analysis (computational theory algorithm/representation, implementation) vs. network architecture and emergent properties  
2) Recurrent networks  
3) Structural scales: functional scales :: kernels: receptive fields  
4) Peak shifts and lateral inhibition  
5) Detectors and filters  
6) Contrast sensitivity and spatial scales

THOUGHT FOR THE DAY

Everybody wants to go to heaven,  
But nobody wants to die.*

Lyrics: Al Fields, Tom Delaney, & Timmie Rogers  
Sung by: Ellen McIlwaine

We the People

New York: Polydor, 1973

*This sentence has a peculiar dissonance after 9/11/2001. Think of it as a statement about modeling.

BACKGROUND FOR TODAY’S TOPICS

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

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

the \textit{Laplacian of a Gaussian} filtering of the image data.

Marr also points out that

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

can be well-approximated by a DOG, if the ratio of excitatory to inhibitory space constants is about 1:1.6.

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

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

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**.

**GROSSBERG’S CRITIQUE OF ZERO-CROSSINGS**

Grossberg (83) prefers to retain the entire output profile of a shunting network with DOG kernels -- as opposed to the zero-crossings of DOG convolutions only:

- **measure of “reflectance”:** amplitude of peak (??) activity among $x_i$'s
- **measure of spatial scale:** the number of spatial nodes affected by an image edge

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**ZERO-CROSSINGS AGAIN**

- **input**
  - Zero-crossings have no height no width.

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

- **$f$**
  - Note: Marr and Grossberg do not disagree on the facts.

- **$f'$**

- **$f''$**

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**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

Hildreth, 1983
CVGIP, 22, 1-27.

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

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

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

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

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

\begin{itemize}
  \item same height: \includegraphics[width=0.2\textwidth]{same_height.jpg} vs \includegraphics[width=0.2\textwidth]{different_height.jpg}
  \item same width \includegraphics[width=0.2\textwidth]{same_width.jpg} vs \includegraphics[width=0.2\textwidth]{different_width.jpg}
\end{itemize}

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

Compare with: “gestalts,” or equilibria (or other characteristics) of complex, nonlinear dynamical systems.

SYMBOLIC AND NONSYMBOLIC PROCESSING

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

- **BLOB**
  - POSITION 146 21
  - ORIENTATION 105
  - CONTRAST 76
  - LENGTH 16
  - WIDTH 6

- **EDGE**
  - POSITION 184 23
  - ORIENTATION 128
  - CONTRAST -25
  - LENGTH 25
  - WIDTH 4

- **BAR**
  - POSITION 118 34
  - ORIENTATION 128
  - CONTRAST -25
  - LENGTH 25
  - WIDTH 6

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?

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)** properties of tokens
- **orientation**
- **density**
- **distance apart**
- **orientation structure** 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.
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”?

WHAT IS REAL?

Principle of least commitment: (Norman)
Don't compute before you have to.
Don't discard information before you need to make a choice.
Q: Is this what Marr does?
(Cf. “What are the units”?)

Zero crossings:
- Easier to understand (and to program)
- Can do striking image processing demos, some can eat up weeks of CPU time
CLAIM: Really real time!

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”

Plug: R. Abraham & C. Shaw
Dynamics: The geometry of behavior
Aerial Press, Inc.
Box 1360, Santa Cruz, CA 95061
(408) 425-8629

PROPERTIES OF RECURRENT COMPETITIVE NETWORKS

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

Possibilities:
- $X \rightarrow 0$ “collapse” of all activity
- $X \rightarrow \infty$
- $X \rightarrow$ constant
- $X \rightarrow$ one of finitely many values
- $X \rightarrow$ 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 \( X_i \to l \) **winner take all** (a.k.a. “choice”)
- All \( X_i \)'s \( \to l/n \) **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?

**RECURRENT, DISTANCE-DEPENDENT NETWORKS**

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

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

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?)
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.

\[
\frac{dx_i}{dt} = -[A + \sum_{k \in i} f(x_k)]x_i + (B-x_i)f(x_i)
\]

I.e. the summations listen in Equations (5) - (8) for \( F_{ii}, F_{ii}, G_{ii}, G_{ii} \) are "no longer operative." But see Ellias & Grossberg (1975).

Let inputs \( K^+, K^- \) 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.

\[
\frac{dx_i}{dt} = -[A + \sum_{k \in i} f(x_k)]x_i + (B-x_i)f(x_i)
\]

Equation (12) of Grossberg (1973)

RESULT: The "shape" of \( f \) makes all the difference concerning the destiny of pattern variables and total network energy.
**GROSSBERG (1973) FAQ 1**

**Q:** What’s the deal with “cell or population”?  
**A:** Assume connections in a network can create “pools” (or “blocks”) of nodes responding identically to the same input. It may be mathematically convenient to treat these pools as single entities.

Possible mechanism for getting around single node saturation limit (upper bound), as in:

\[(B-x)(\text{excitatory terms}).\]

**GROSSBERG (1973) FAQ 2**

**Q:** When can you solve directly for the equilibrium state of a differential equation by setting derivative to zero and solving resulting algebraic equation?

**A:** First ask: Am I sure that any equilibrium exists? If so, is there only one? Moreover, is the system governed by the equation uniformly asymptotically stable, with a single attractor?

This is unlikely, to say the least, for large, nonlinear, recurrent networks.

**WHY GROSSBERG (1973)?**

Why discuss Grossberg (1973) at this point in CN530?

Recall: At the conclusion of Week 1’s lecture:

In the visual universe, we have:  
- coherence from disconnected elements, and  
- segmentations through homogeneous regions!

What kind of geometry does this?  
What could possibly be its functional units?

Consider a “Miller analogy:”

**GROUPING:** (e.g. in Glass or Bozzi patterns) perceived wholes are more uniform than their underlying luminance distributions.  
**SEGMENTATION:** (e.g. Beck textures, Ehrenstein figures) perceived segmentations selectively cut through parts of homogeneous luminance regions.

**ROOTS**

Many of the developments of the vision theory developed by Grossberg and colleagues from the 1980's through the present were foreshadowed in Grossberg (1983).

They can be viewed as harnessing the intuitions of theorems on recurrent (feedback) networks first explored in Grossberg (1973), but in networks with increasingly elaborate distance-dependent interactions (kernels).
STRUCTURAL AND FUNCTIONAL SCALES

The measured magnitudes of perceptual phenomena (e.g., the strength of the café wall illusion) may not be as directly “readable” from the sizes of anatomical structures, . . . as would be the case if the visual system were more “linear.”

- anatomy
- physiology
- geometry
- dynamics
- structural scales
- functional scales

STRUCTURAL AND FUNCTIONAL SCALES AGAIN

In a network model, a kernel defines a structural scale: e.g., a Gaussian of unit weight, $\sigma = 2$, truncated at 5 nodes from center.

The functional scale of this network’s response to inputs of varying sizes might need to be determined by simulation, if the network involves nonlinear feedback (no analytic solution.)

I.e., how many nodes have their activity affected (either excitation or inhibition) as a function of bar thickness?

CONTEXT DEPENDENCE

The measured size of many cells’ receptive fields depend on the nature of (current and prior) stimulation.

For feedforward anatomies, structural and functional scales may be (more or less!) directly related.

Once feedback or recurrent (including lateral) connections occur, functional scales become much more “interesting.”

FUNCTIONAL SCALES AND PEAK SHIFT

Consider Blakemore et al.’s (1970) angle expansion illusion, as described by Levine and Grossberg (1976):

“If two lines forming an acute angle are presented to a subject and he is asked to place a third line parallel to the other two, he will err in the direction of perceiving the angle as larger than it really is:”

Recall: Poggendorf illusion

Blakemore et al.’s hypothesis: Shift in perceived angle is due to lateral inhibition among cortical neurons that are tuned to different orientations of contrast.
LATERAL INHIBITION AND PEAK SHIFTS

Levine & Grossberg (1976): a node’s preferred angle-of-contrast is coded by its position within network ==> “on-center, off-surround” in orientation space.

Response of network to a single input at 0°.

Response of network to a single input at 10°.

The peak responses shift “outward” from corresponding single-input locations when 0° and 10° inputs occur simultaneously.

Note: These “hand-made” graphics predate MATLAB!

VARIEITES OF LATERAL INHIBITION

Levine and Grossberg (1976) goals: Classify outcomes of different kinds of “lateral inhibition:”

- additive

\[ \frac{dx_i}{dt} = -Ax_i + \sum_{m=1}^{n} K_m C_{mi} - \sum_{m=1}^{n} K_mD_{mi} \quad \text{Eq. (10), p. 486} \]

- shunting, feedforward, no hyperpolarization

- shunting, feedforward, with hyperpolarization

- shunting, feedback

ANATOMIES OF COMETITIVE NETWORKS

Feedforward:

With-layer (a.k.a. “horizontal” or “lateral”) feedback (recurrent)

Between-layer feedback (recurrent)

Notational remark: In L & G, 1976, p. 487

\[ I_i = K_mC_{mi} \]

implies that a Gaussian weighting of inputs, (as well as of feedback signals) exists.

Also, PUN ALERT: “net inhibition”
INFERENCES FROM DATA

Q: Does the empirical observation of a peak shift in vivo imply that subtractive inhibition must be occurring?

Consider L & G’s Eq. 13:

\[ x_i = \frac{\sum_{m=1}^{n} K_m (B C_{m_i} - E D_{m_i})}{A + \sum_{m=1}^{n} K_m (C_{m_i} + D_{m_i})} \]

Of what differential equation is this the equilibrium solution?

If \( E = 0 \):
No hyperpolarization, therefore no “net” inhibition -- i.e., “direct, subtractive” inhibition -- occurs via DOG in numerator.

L & G claim: Peak shift can still occur . . .
with only divisive effect of \( I_2 \) through \( D_{m_i} \).

FEEDBACK AND TIME

In a simulation of a recurrent network, G & L demonstrate the importance of temporal factors in the “balance” of excitation and inhibition.

“Fig 10 Inward peak shift [], indicated by heavy dots in figure, becomes outward as recurrent inhibition “builds up” over time!”

Think about “structural vs. functional scales.”

INFERENCES CONTINUED

ON THE ROAD

BAD NEWS: We’re lost!
GOOD NEWS: We’re making good time!

Week 1: Overture
Week 2: Simple shunting networks
Week 3: Grossberg/Marr debate
Structural and functional scales
More shunting network background

X You are here.
Linear systems in vision
Filters and detectors

Week 4: Basic physiology
Approaches to brightness perception

When do we find out what the units of vision are?
GRAINS OF ANALYSIS

What are the appropriate *grains* of measurement and analysis for studying intelligent processes?  
(See Schwartz, Bonus Reading, Week 4.)

1) **Synapse** (biochemistry, biophysics)
2) **Neuron** (and neural networks)
3) **Columns** and **maps**
4) **Behavior**

What inferences are available *across* grains? E.g., how can data at one grain constrain modeling at another?

SOBERING THOUGHTS


In fact, as many kinds of mathematics seem to be applied to perception as there are problems in perception. I believe this multiplicity of theories without a reduction to a common core is inherent in the nature of psychology . . ., and we should not expect the situation to change. The moral, alas, is that we need many different models to deal with the many different aspects of perception.

Q: What is going on when “many different models” are applied to the same “aspect[s] of perception”?

FEATURE DETECTION

Common theme in vision:

Scenic input is *too* rich in (bits of) information; the visual system has no choice but to perform some kind of *image decomposition*, to “extract” the important information.

Barlow (1953) introduced the idea of “trigger features” for cell responses.

Hubel & Wiesel (1959, etc.) extended the range of *feature detector* theories of visual processing.

Observation: Certain cortical cells appear to respond best (in some cases almost exclusively) to simple but specific image features (e.g. edges, line ends, corners).

Thanks, Paolo!

Many of the following panels are based on notes originally developed by Paolo Gaudiano for an earlier edition of CN 530.
THE “GRANDMOTHER CELL” MODEL

Hubel and Wiesel developed a **hierarchical** model of organization of visual cortex -- still an influential view -- in which successive layers of cells respond to specific **combinations** of features coded by a previous layer.

Cf: Selfridge’s (1959) Pandemonium model of cognitive processes:

"Grandma!"

"... and then, a miracle occurs."

- hyper-complex
- hyper-complex
- hyper-complex
- complex
- complex
- complex
- simple
- simple
- simple

**NEOCOGNITRON**

Compare Fukushima’s Neocognitron model (shift-tolerant feature extraction and classification)

**FEATURE DETECTOR HIERARCHY?**

Some physiological evidence argues against the **hierarchical** scheme. E.g., many complex cells become activated before simple cells upon input presentation. Seems to invalidate:

- complex
- simple

Much of cortical organization is **parallel**.

Q: **parallel as opposed to** hierarchical, or **parallel in addition to** hierarchical?

**MODELING AS POETRY**

Is the idea of visual cortical cells as **feature detectors*** the right metaphor. (Yes, I said metaphor.)

What else could they be?

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*The word “feature” is used in many, and contradictory ways in the field of vision.*
DETECTORS VS. FILTERS

A detector ("active") responds only to the presence of "specific tokens" or "signature patterns" in an image.

A filter ("passive") responds to any input token -- up to the limits of the filter's resolution or range -- but gives strongest responses to a small (?) range of token values.

Consider: You would want an "unbroken line detector" to respond to this, but not to this.

This result is hard to achieve (over variations in contrast, etc.) with a conventional ("convolution") filter.

Is this just a question of semantics?
I.e., is the distinction a matter of definition of "specific tokens" vs. "small range of token values."

Is a detector just a "filter with a threshold"?

Sociology of science: Whether one speaks of visual cortical cells as detectors or as filters is correlated with the field of study in which a researcher earns academic degrees!

FILTERS AND TRANSFER FUNCTIONS

Consider a filter as a "black box" that transforms each input into some output:

If the value of the output exhibits some systematic relationship with some measurable aspect of the input, we can speak of the transfer function of the filter.

CONTRAST DETECTION AND SPATIAL FREQUENCY

Cornsweet (1970) describes the visual system as consisting of a single "channel" -- which acts as a filter whose response depends (in part) on the spatial frequency content of the image.

Cornsweet writes of a modulation transfer function (MTF) because the measure of the input that is plotted against output is the modulation of the luminance of the image ("intensity").
Historical note re: “sinusoidal grating”
A grating is a tool used in optics for the study of diffraction and interference of light; it is a surface (film) with slits etched on it.
A simple two-slit grating can be used to generate sinusoidal modulations in luminance.
Today, “sine wave gratings” are generally computer generated images.

SPATIAL FREQUENCY

Periodic stimuli can be classified by the spatial frequency of the modulation of their luminance.

Spatial frequency: the number of times (cycles) that luminance changes from some minimum to some maximum value over a fixed distance, given in degrees of visual angle.

Image regions containing only low spatial frequencies generally look relatively homogeneous; those containing only high spatial frequencies generally appear to have a lot of “detail” or “texture.”

Q. What is the relationship of spatial frequency to Grossberg's usage of the word “scale”?

HUMAN POINT SPREAD FUNCTION

Assume that the eye is a perfect lens, ignoring: spherical aberration, chromatic aberration, diffraction, scatter, . . .

The imperfections can be usefully “accounted for,” paving the road for spatial frequency methods, and attendant formalisms (e.g. linear systems theory; Fourier analysis and synthesis, wavelets, etc.)
POINT SPREAD FUNCTION AGAIN

Fig. 3.21 Diffraction of light by the pupil of the eye. The width of the retinal light distribution is exaggerated. (From Cornsweet, 1970.)

Fig. 3.27 Light distribution on the retina for a fine bright line object, calculated from the curve in Figure 3.26. The black rectangle represents the diameter of a retinal receptor in the central fovea. [After Westheimer and Campbell (1962), subject J. K. 3 mm pupil.] (From Cornsweet, 1970.)

NOTE: We can perceptually “resolve” displacements of thin lines at distances smaller than the diameter of a single photoreceptor!

SINUSOIDAL GRATINGS

The visual system can be probed by measuring its response to stimuli that contain only one spatial frequency, or a carefully controlled combination of stimuli at specific spatial frequencies.

Strategy: For measuring an unknown system, make your probe as simple as possible, and know all of the probe’s characteristics with respect to dimensions of measurement.

Tradeoff: “Ecological validity” -- where did you last see (only) stripes with sinusoidal luminance modulation?

HUMAN MODULATION TRANSFER FUNCTION (MTF)

Sinusoidal stimuli are used to measure the threshold response of the human visual system as a function of spatial frequency.

To be found: minimum contrast necessary to detect the presence of a sinusoidal modulation of luminance of a certain spatial frequency

HUMAN MTF

Fig. 12.13 The solid curve is a describing function of the human visual system, obtained by measuring the threshold modulation at each spatial frequency. (100% modulation means that the troughs of the sine wave are completely dark.) The dashed curve is what would be expected for a lens under the same conditions of testing.

[The solid curve is from Van Nes and Bouman (1965); $l = 525$ nm, average intensity = 90 trolands.] (Adapted from “where else”?!)

resulting MTF:
CAMPBELL-ROBSON CONTRAST- SENSITIVITY DEMO AT
http://www.bpe.es.osaka-u.ac.jp/ohzawa-lab/izumi/CSF/A_JG_RobsonCSFchart.html

MTF & CSF

Modulation transfer function (MTF)
Contrast sensitivity function (CSF)

The more modulation you need to detect a grating at a given frequency, the less sensitive you are to contrast at that frequency.

THRESHOLD CONTRAST FOR DETECTION

Gabori Attack!!

Download Gabori Attack (Mac/Windows)

Do you or do you not see anything on this trial?
The question appears binary, but do the processes involved in exceeding a sensory threshold behave like step functions?

response

yes

no

stimulus magnitude

SIGNAL DETECTION THEORY

Instead: Consider threshold sensitivity as a stochastic process, and use concepts from signal detection theory.

The placement of the criterion level for output of positive response depends on “payoffs” for false positives vs. misses in signal-present cases.
SIGNAL DETECTION METHODS

Common assumptions:

1) **Normal distribution** of sensor activity

2) **Same variance** of sensor activity with or without signal present

3) **Known receiver characteristics** (e.g., transfer function)

For multi-channel detectors, add:

4) assumptions about **superposition or probability summation** for responses of separate channels into a single “yes or no” output (See Graham, supplementary, Week 5)

Just as with kernels and receptive fields, “thresholds” are

• trivial to set in a network simulation, and

• difficult to measure in real life.

SUPRATHRESHOLD PERFORMANCE

Query: If the visual system is so much more sensitive in the middle spatial frequencies than at the extremes, why is it that, along the bottom of the figure, where you can notice the contrast modulation across virtually the entire frequency range, the resulting modulation of **brightness** is essentially **homogeneous throughout that frequency range**?!

In other words: **What are the units** of brightness perception?

There are subtleties of usage of terms in the previous slide that I do not expect you to “get,” if for no other reason than that experts in the field use the terms in inconsistent ways. This is certainly true of brightness and lightness, as applied to perceptual phenomena.

What I do expect you to demonstrate an understanding of, through the way in which you choose words, is a sensitivity to language that is appropriate for describing a stimulus, and language that is appropriate for describing a percept.

LEARN THIS TERMINOLOGY*!!!

**Photometric** measures of light intensity reaching some point (employed in neurophysiology and psychophysics) are weighted by human sensitivities (optics of cornea, lens, pigment absorption spectra, etc.) while **radiometric** measures (physics) do not. (Energy that does not stimulate human photoreceptors does not count for photometric measures.)

**Illuminance** is the amount of visually effective light falling on a surface. (That light may or may not ever reach a photoreceptor!)

**Luminance** is the amount of visually effective (photometric) light emitted by some source (or, in practice, reflected off some surface).

**Brightness** is (used by many to mean) a subjective measure of sensation associated with the magnitude of luminance of a stimulus patch viewed in isolation on a surround of zero luminance. (DIM to BRIGHT.) Related (?) usage: “Subjective estimate” of luminance (!) of an area of a scene.

**Lightness** is (used by many to mean) a subjective measure of the relative “gray value” of a luminance patch, viewed on a surround of nonzero luminance. (DARK to LIGHT, or BLACK to GRAY to WHITE). Related (?) usage: “Subjective estimate” of reflectance of a surface area. (Adapted from Uttal, 1976)

*Points on mid-term examination hang in the balance.