I’m very grateful to have the opportunity to speak to you today, but I do so while feeling deep sadness and grief about the tragic loss of life and health due to the coronavirus pandemic, and the economic devastation that it has unleashed upon millions around the world.

These feelings have only deepened as the Original Sin of systemic racism has traumatized the United States once again, and galvanized concerned citizens around the world to demand that black and brown people be finally given equal opportunities and justice.

Scientific truth and progress have the power to guide us steadily to a better future. Let us dedicate ourselves to realizing the hope that they will continue to do so.
From designs for autonomous adaptive agents to clinical disorders: Linking cortically-mediated learning to Alzheimer’s disease, autism, amnesia, and sleep

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Center for Adaptive Systems
Graduate Program in Cognitive and Neural Systems
Department of Mathematics & Statistics, Psychological & Brain Sciences, and Biomedical Engineering
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sites.bu.edu/steveg
HOW CAN A TALK ON THIS TOPIC EVEN BE GIVEN?

The results are based on the most advanced neural models of HOW OUR BRAINS SEE, RECOGNIZE, AND PREDICT objects and events in a changing world

The models emerged through 50 years of research

They also offer an explanation of what goes on in each brain as it consciously sees, hears, feels, or knows
HOW MUCH PROGRESS HAS BEEN MADE?

It has led to a major scientific PARADIGM SHIFT that has required

- new design principles that unify multiple disciplines
- new mathematical concepts and methods
- major computer resources
- multiple experimental techniques
WHAT IS THIS PARADIGM SHIFT?

It began in the late 1800’s
when great scientists such as Helmholtz, Maxwell, and Mach
worked in both psychology and physics

This shift accelerated in the 1970’s - 1980’s
See Grossberg (1988, Neural Networks, 1, 17)

This paradigm shift is about:

Understanding how an individual adapts on its own in real time to a complex and changing world

AUTONOMOUS adaptation to a changing world filled with unexpected events

For AI, designs for autonomous adaptive intelligence
My own work focuses on

**HOW DOES A BRAIN GIVE RISE TO A MIND?**

Link Brain MECHANISMS to Mental FUNCTIONS

What level of brain organization controls behavior?
What is the functional unit of behavior?

**BRAIN evolution needs to achieve BEHAVIORAL success**

What level of BRAIN processing governs BEHAVIORAL success?

The **NETWORK and SYSTEM levels**!
Why we study neural networks
At every stage, spin off new model designs and mechanisms to technologists who need autonomous adaptive intelligence.
TRUE THEORIES ARE EMERGING

A small number of equations
e.g., shunting activation dynamics (STM)
habituative transmitter gates (MTM)
activity-gated learning (LTM) …

A larger number of modules*
e.g., on-center off-surround nets
resonant matching nets
opponent processing nets
spectral timing nets
boundary completion nets
filling-in nets…

Specialized combinations of modules*, using a few basic equations, are assembled in architectures that solve modal problems

A still larger number of modal architectures
e.g. vision
audition
smell
touch
cognition
emotion…

Modules are microcircuits, not the “independent modules” of AI
Predictive ART, or pART, architecture macrocircuit
How prefrontal cortex learns to control all higher-order intelligence
Grossberg (2018; see sites.bu.edu/steveg)

Working memory, learned plans, prediction, optimized action

Reinforcement learning, emotion, motivation, adaptively-timed learning,

Visual perception, category learning, object attention
WHAT PRINCIPLES DETERMINE HOW MODAL ARCHITECTURES ARE DESIGNED?
BREAKTHROUGHS IN BRAIN COMPUTING

Models that link detailed BRAIN CIRCUITS to the ADAPTIVE BEHAVIORS that they control

- Mind/Body Problem
- INDEPENDENT MODULES
- Computer Metaphor

Describe NEW PARADIGMS for brain computing

COMPLEMENTARY COMPUTING
What is the nature of brain specialization?

LAMINAR COMPUTING
Why are all neocortical circuits organized in layers?
How do laminar circuits give rise to biological intelligence?
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Computer Metaphor

COMPLEMENTARY COMPUTING

What is the nature of brain specialization?

LAMINAR COMPUTING

Why are all neocortical circuits organized in layers? How do laminar circuits give rise to biological intelligence?
A KEY RESEARCH GOAL

Develop a comprehensive theory of how laminar neocortical circuits are specialized for different types of intelligence
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Develop a comprehensive theory of how laminar neocortical circuits are specialized for different types of intelligence.

3D Vision 3D LAMINART
Speech cARTSCAN
Cognition LIST PARSE

These models use specializations of the same canonical laminar circuitry:
An Existence Proof!

Grossberg (2013; see sites.bu.edu/steveg)
A self-organizing VLSI chip set whose modules are computationally consistent and can therefore be assembled into autonomous adaptive agents to carry out multiple intelligent tasks.

A potentially huge technological impact in multiple areas of intelligent computation.
BREAKTHROUGHS IN BRAIN COMPUTING

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Mind/Body Problem

Describe NEW PARADIGMS for brain computing

INDEPENDENT MODULES Computer Metaphor

COMPLEMENTARY COMPUTING
What is the nature of brain specialization?

LAMINAR COMPUTING
Why are all neocortical circuits organized in layers?
How do laminar circuits give rise to biological intelligence?
New principles of UNCERTAINTY and COMPLEMENTARITY clarify why

Multiple parallel processing streams exist in the brain

Lots of specialization!
WHAT ARE COMPLEMENTARY PROPERTIES?

Analogies:
Key fits lock, puzzles pieces fit together

Computing one set of properties at a processing stage prevents that stage from computing a complementary set of properties

Complementary parallel processing streams are BALANCED against one another

INTERACTIONS between streams overcomes their complementary weaknesses and support intelligent and creative behaviors
<table>
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WHAT IS A VISUAL BOUNDARY OR GROUPING?

Illusory contour

Texture pop-out

3D shape from texture

Figure-ground separation
VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY

BOUNDARY COMPLETION

oriented inward
insensitive to direction-of-contrast

SURFACE FILLING-IN

unoriented outward
sensitive to direction-of-contrast

Neon color spreading

Grossberg (1984)

Neon color spreading
DeYoe and van Essen (1988)
VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY

Grossberg (1984)

Neon color spreading

BOUNDARY COMPLETION

SURFACE FILLING-IN

What about

oriented inward
insensitive to direction-of-contrast

unoriented outward
sensitive to direction-of-contrast
SEEING vs. KNOWING

SEEING an object

Epstein, Gregory, Helmholtz, Kanizsa, Kellman, Michotte, …

KNOWING what it is

SEEING

Ehrenstein Figure

See

Recognize

vs.

RECOGNIZING

Offset Grating

Some boundaries are invisible, or amodal

Do not see

Recognize

SG/WCCI/20
ALL BOUNDARIES ARE INVISIBLE!
within the Boundary Stream
Grossberg (1984)

WHY? To recognize object boundaries in front of textured backgrounds
ALL BOUNDARIES ARE INVISIBLE: COMPLEX CELLS

Complex cells pool inputs from opposite-polarity simple cells in V1

VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY

BOUNDARY COMPLETION
- oriented inward
- insensitive to direction-of-contrast

SURFACE FILLING-IN
- unoriented outward
- sensitive to direction-of-contrast

Neon color spreading

All Boundaries Are Invisible!
IF BOUNDARIES ARE INVISIBLE, HOW DO WE SEE?

*Filling-In* of Surface Color

Boundaries define the compartments within which lightness and color spread

Ehrenstein (1941)  
Varin (1971)
Craik-O’ Brien-Cornsweet Effect

Boundary completion defines filling-in compartments

Filling-in determines what we see in each compartment

Grossberg (1984)
Todorović (1987)
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Neon color spreading

Filling-in of Visible Color and Lightness

SG/WCCI/20
PREDICTIONS

Grossberg (1984)

ALL BOUNDARIES ARE INVISIBLE
in the interblob stream

VISIBLE QUALIA ARE SURFACE PERCEPTS
in the blob stream
THIS IS A TALK IN TWO PARTS

The first part:
Acetylcholine neuromodulation in normal and abnormal learning and memory: Vigilance control in waking, sleep, autism, amnesia, and Alzheimer’s disease.

Article with the same title published OPEN ACCESS in 2017 in *Frontiers in Neural Circuits*; also on my web page sites.bu.edu/steveg

This work illustrates the importance of BALANCING PARAMETERS, i.e., homeostatic regulation to generate adaptive behaviors.

SG/WCCI/20
A unifying theme of this part of the talk is **VIGILANCE CONTROL** and how it can break down during various mental disorders.
A unifying theme of this part of the talk is VIGILANCE CONTROL and how it can break down during various mental disorders.

Most discussions of Alzheimer’s disease focus on the terrible STRUCTURAL degeneration that occurs.

I will explain how these structural events may affect the DYNAMICS of learning, recognition, and cognition during the disease.

Model provides a LINKING HYPOTHESIS between STRUCTURE and FUNCTION (SYMPTOMS).
LOTS OF EXPERIMENTAL EVIDENCE FOR STRUCTURAL EVENTS THAT SEEM TO CAUSE ALZHEIMER’S

Beta-amyloid plaque and neurofibrillary tangles are implicated
Dickson, 1997; Godert, 1993; Hardy and Allsop, 1991; Ikeda et al., 1987; Lacor et al, 2007; Poksay et al., 2017

Anti-amyloid antibodies, BAN2401 and aducanumab, slow disease
Lannfelt et al., 2014; Logovinsky et al., 2016; Mendes & Palmer, 2018
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How do these structural events cause the DYNAMICS of LEARNING, MEMORY, and COGNITION to collapse?
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How do these structural events cause the DYNAMICS of LEARNING, MEMORY, and COGNITION to collapse?

VERY COMPLICATED!
But here is one line of experiments and an explanation of them

This explanation also clarifies links between Alzheimer’s and DISORDERED SLEEP
PLAQUES AND TANGLES DISRUPT ACh FUNCTION

Plaques and neurofibrillary tangles primarily in layers 3 and 5
Tomlinson et al., 1968; Arnold et al., 1991

Nucleus basalis of Meynert sends ACh-releasing neurons to layer 5
Saar et al., 2001; Zhang et al., 2004

Cholinergic agonists produce cognitive improvement in Alzheimer’s
Zhang et al., 2004

α7 nicotinic ACh receptor (α7nAChR) is highly expressed
in basal forebrain neurons that project to cortex
Perry et al., 1992

The 42-amino acid β-amyloid peptide (Aβ1-42)
binds with high affinity to α7nAChR
and accumulates in Alzheimer patient neurons
This peptide inhibits release of ACh
Kar et al., 1996
ACh-releasing neurons with cell bodies in basal forebrain degenerate
Coyle, Price, and DeLong (1981)

Postmortem studies demonstrate profound reduction
in presynaptic markers for ACh neurons in Alzheimer’s patients
Whitehouse et al. (1982)

Alzheimer’s animal models show that anticholinergic drugs and nucleus
basalis lesions disrupt learning or memory in multiple paradigms
including passive avoidance learning and Morris water maze
Friedman, Lerer, and Kuster, 1981; LoConte et al., 1982;
Francis et al., 1999; Iqbal and Grundke-Iqbal, 2008; Pimplikar, 2009
Acetylcholinesterase (AChE) is the main enzyme to break down ACh. Inhibition of AChE is used to ameliorate Alzheimer’s symptoms. Mukherjee et al., 2007; Orban et al., 2004

Extensive network of cortical pyramidal neurons in human brain with AChE activity.

Adults above age 80 with excellent memories (SuperAgers) show much lower staining of AChE neurons compared with same-age peers. Low AChE could counterbalance declining memory during normal aging. Janeczek et al., 2017

Zizypus jujube (ZJ) activates choline acetyltransferase (ChAT), an enzyme that induces ACh synthesis. Used ZJ in a rat model of Alzheimer’s with nucleus basalis lesions. ZJ has repairing effects on memory and behavioral disorders. Rabiei et al., 2014
HOW DO THESE NUCLEUS BASALIS AND ACh PROBLEMS AFFECT LEARNING, MEMORY, AND COGNITION?

They cause a breakdown of both TONIC and PHASIC VIGILANCE CONTROL

VIGILANCE CONTROL regulates learning, recognition, and cognition

TONIC vigilance sets the baseline of cortical sensitivity

PHASIC vigilance changes are triggered by unexpected events that drive new learning

In this regard, Alzheimer’s patients have lower levels of overall vigilance and poorer concentration to stimuli over time than controls

Bernardi, Parsuraman, and Haxby, 2005
ADAPTIVE RESONANCE THEORY

ART
Grossberg (1976)

A unifying theme:

Stability-Plasticity Dilemma

How can learning continue into adulthood without causing catastrophic forgetting?

How can we LEARN quickly without being forced to FORGET just as quickly?

e.g., why learning your faces does not force me to forget faces of my family and friends!
Predictive ART, or pART, architecture macrocircuit
How prefrontal cortex learns to control all higher-order intelligence
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RECENT HEURISTIC REVIEW ARTICLES OF ART AS A COGNITIVE AND NEURAL THEORY

sites.bu.edu/steveg


ART HELPS TO SOLVE AN OLD PROBLEM

Why do we pay attention?

Why do we learn expectations about the world?

Role of top-down processing

Helmholtz  Unconscious Inference
William James  Pragmatism
Tolman  Learn Expectations
Gregory  Cognitive Contours
Top-down attentive feedback encodes learned expectations that dynamically stabilize learning and memory in response to a rapidly changing world that is filled with unexpected events.

Attentive Information Processing

Learning and Memory

FAST

SLOW
ART WORKS!
Large-scale applications in engineering and technology

techlab.bu.edu

Boeing parts design retrieval (used to design Boeing 777)
satellite remote sensing
radar identification
robot sensory-motor control and navigation
machine vision
3D object and face recognition
Macintosh operating system software
automatic target recognition
ECG wave recognition
protein secondary structure identification
character classification
musical analysis
air quality monitoring and weather prediction
medical imaging and database analysis
multi-sensor chemical analysis
strength prediction for concrete mixes
signature verification
decision making and intelligent agents
machine condition monitoring and failure forecasting
chemical analysis
electromagnetic and digital circuit design
WHY IS ART USED IN SO MANY APPLICATIONS?
It has desirable learning properties that other models do not.

Contrast Deep Learning

Learn rare events
need fast learning

Learn large non-stationary data bases
need self-stabilizing learning and memory

Learn morphologically variable events (concrete/abstract)
need multiple scales of generalization: vigilance!

Learn many-to-one and one-to-many relationships
need categorization, naming, and expert knowledge
# LEARN MANY-TO-ONE and ONE-TO-MANY MAPS

**Many-to-One (DL)**

<table>
<thead>
<tr>
<th>Compression, Naming</th>
<th>One-to-Many (Expert Knowledge)</th>
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<tbody>
<tr>
<td>$(a_1,b)$</td>
<td>$(a,b_1)$</td>
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</tr>
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<td>$(a_4,b)$</td>
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**Fruit**

- Apple
- Banana
- Orange
- Grapes

**Animal**

- Mammal
- Pet
- Dog
- Dalmatian
- Fireman’s Mascot
- “Rover”
ARTMAP PROPERTIES

To realize these properties, ARTMAP systems:

Learn self-stabilizing recognition categories
solve the catastrophic forgetting problem

Pay attention
ignore masses of irrelevant data

Test hypotheses (self-organizing production system)
discover predictive constraints hidden in data streams

Choose best answers (solve local minimum problem)
direct access to globally optimal solution at any time

Calibrate confidence
measure on-line how well a hypothesis matches the data

Discover rules, and hierarchies of cognitive rules
identify transparent IF-THEN rules on each learning trial

Scale
all properties hold for arbitrarily large databases
ART vs. BACK PROPAGATION and DEEP LEARNING

Grossberg, 1988, *Neural Networks*, 1, 17-61, Section 17

17 basic differences between BP and brain learning sites.bu.edu/steveg

A. Real-Time (On-Line) Learning versus Lab-Time (Off-Line) Learning
B. Nonstationary Unexpected World Versus Stationary Controlled World
C. Self-Organization Versus Teacher as a Source of Expected Output
D. Self-Stabilization Versus Capacity Catastrophe
E. Maintain Plasticity on an Unexpected World versus Externally Shut Off Plasticity
F. Self-Scaling Computational Units
G. Learn Internal Expectations Versus Impose External Costs
H. Active Attentional Focusing and Priming Versus Passive Weight Change
I. Closing Versus Opening the Fast-Slow Feedback Loop
J. Expectant Priming Versus Grinding All Memory Cycles
K. Learning in the Approximate Match Phase Versus in the Mismatch Phase: Hypothesis Testing Avoids the Noise Catastrophe
L. Fast or Slow Learning: The Oscillation Catastrophe
M. Self-Adjusting Parallel Memory Search Trees and Global Energy Landscape Upheaval Versus Search Trees and Local Minima
N. Rapid Direct Access Versus Increase of Recognition Time with Code Complexity
O. Asynchronous Versus Synchronous Learning
P. Discriminative Tuning via Attentional Vigilance
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   Data Search, and Classification
EARLY ARTMAP BENCHMARK STUDIES

Database benchmark:
  MACHINE LEARNING (90-95% correct)
  ARTMAP (100% correct on a training set an order of magnitude smaller)

Database benchmarks:
  BACKPROPAGATION (10,000 – 20,000 training epochs)
  ARTMAP (1-5 epochs)

Medical database:
  STATISTICAL METHOD (60% correct)
  ARTMAP (96% correct)

Letter recognition database:
  GENETIC ALGORITHM (82% correct)
  ARTMAP (96% correct)

Used in applications where other algorithms fail
  e.g. Boeing CAD Group Technology
    Part design reuse and inventory compression
    Need fast (e.g., 1 trial and stable learning and search of a huge
    (16 million 1 million dimensional vectors) and continually growing
    non-stationary parts inventory

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AI Expert system – 1 year

Field identification of natural regions
Derivation of ad hoc rules for each region, by expert geographers
Correct 80,000 of 250,000 site labels
230m (site–level) scale

ARTMAP system – 1 day

Rapid, automatic, no natural regions or rules
Confidence map
30m (pixel–level) scale: can see roads
Equal accuracy at test sites
INFORMATION FUSION IN REMOTE SENSING
Carpenter et al. (2004)

Multimodal integration of information from many sources to learn a knowledge structure:
CONSISTENT
STABLE
ROBUST
LEARNED ONLINE
SELF-ORGANIZED

Boston testbed
PROBLEM: Integrate multiple sources into a coherent knowledge structure

Solution 1:
HUMAN MAPPING EXPERT:
Slow, expensive, possibly unavailable

Solution 2:
Distributed ARTMAP MODEL:
Fast, automatic, easy to deploy
NO PRIOR RULES OR DOMAIN KNOWLEDGE

Self-organizing expert system
SELF-ORGANIZES a HIERARCHY of COGNITIVE RULES

Distributed predictions across test set pixels

RULE DISCOVERY

Confidence in each rule = 100%, except where noted

CONSISTENT MAPS, LABELED BY LEVEL

Boston testbed
ART MATCHING AND RESONANCE RULES
help to solve the Stability-Plasticity Dilemma

BOTTOM-UP ACTIVATION
by itself can activate learned categories
(automatic activation)

TOP-DOWN EXPECTATIONS
learn prototypes that
select consistent bottom-up signals
(hypothesis testing)
suppress inconsistent bottom-up signals (attentional focusing)
cannot by themselves fully activate
target cells (sensitize, modulate, prime)
EXPECTATIONS FOCUS ATTENTION

Categories (STM)

Bottom-up adaptive filter (LTM)

Distributed feature pattern (STM)

STM before top-down matching

STM after top-down matching

Attention!
Why are LEARNED TOP-DOWN EXPECTATIONS and ATTENTION needed to solve the STABILITY-PLASTICITY DILEMMA?
COMPETITIVE LEARNING AND SELF-ORGANIZING MAPS

Categories
Compressed STM representation
competition

Adaptive Filter $T=ZS$

Features
Distributed STM representation

If a sequence of feature patterns does not form too many clusters relative to the number of category coding cells, then learning is

- stable
- self-normalizing
- tracks input statistics
- Bayesian
STABLE SPARSE LEARNING THEOREM

Grossberg, 1976

If a sequence of feature patterns does not form too many clusters relative to the number of category coding cells, then learning is

stable
self-normalizing
tracks input statistics
Bayesian

In general, learning is unstable in response to a dense series of inputs whose statistics change through time.

Recent learning can force unselective forgetting or catastrophic forgetting of older learning.
ART was introduced to dynamically stabilize recognition learning using top-down EXPECTATIONS and ATTENTION.

Cf. experiments of C. Gilbert, E. Kandel, M. Merzenich, etc.
ART was introduced to dynamically stabilize recognition learning using top-down EXPECTATIONS and ATTENTION.

Cf. experiments of C. Gilbert, E. Kandel, M. Merzenich, etc.

HOW do expectations focus attention and stabilize learning?
ART MATCHING RULE FOR OBJECT ATTENTION

Stabilizes Learning

Top-down, modulatory on-center, off-surround network

Carpenter and Grossberg (1987, CVGIP) and many later articles
ART MATCHING RULE FOR OBJECT ATTENTION

Stabilizes Learning

Top-down, modulatory on-center, off-surround network

Categories

Features

Volition

One against one

Two against one

Carpenter and Grossberg (1987, CVGIP) and many later articles

SG/WCCI/20
LAMINAR CORTICAL CIRCUIT FOR OBJECT ATTENTION

Grossberg (1999, Spatial Vision)

Attention acts via a TOP-DOWN MODULATORY ON-CENTER OFF-SURROUND NETWORK
LAMINAR CORTICAL CIRCUIT FOR OBJECT ATTENTION

Grossberg (1999, Spatial Vision)

INTRA cortical feedback from groupings
INTER cortical attention

Attention acts via a TOP-DOWN MODULATORY ON-CENTER OFF-SURROUND NETWORK
SUPPORT FOR ART PREDICTIONS

ATTENTION HAS AN ON-CENTER OFF-SURROUND

Bullier, Jupe, James, and Girard, 1996
Caputo and Guerra, 1998
Downing, 1988
Mounts, 2000
Reynolds, Chelazzi, and Desimone, 1999
Smith, Singh, and Greenlee, 2000
Somers, Dale, Seiffert, and Tootell, 1999
Sillito, Jones, Gerstein, and West, 1994
Steinman, Steinman, and Lehmkuhne, 1995
Vanduffell, Tootell, and Orban, 2000

“BIASED COMPETITION”

Desimone, 1998
Kastner and Ungerleider, 2001
ATTENTION CAN FACILITATE MATCHED BOTTOM-UP SIGNALS

Hupe, James, Girard, and Bullier, 1997
Luck, Chellazi, Hillyard, and Desimone, 1997
Roelfsema, Lamme, and Spekreijse, 1998
Sillito, Jones, Gerstein, and West, 1994
and many more...

INCONSISTENT WITH MODELS WHERE TOP-DOWN MATCH IS SUPPRESSIVE

Mumford, 1992
Rao and Ballard, 1999

Bayesian Explaining Away
ADAPTIVE RESONANCE

Attended feature clusters reactivate bottom-up pathways

Activated categories reactivate their top-down pathways

Feature-Category resonance synchronizes
amplifies
prolongs system response

Resonance triggers learning in bottom-up and top-down
adaptive weights: adaptive resonance!
ALL THE KEY ART PREDICTIONS HAVE BEHAVIORAL AND NEUROBIOLOGICAL SUPPORT

ALL CONSCIOUS STATES ARE RESONANT STATES

Grossberg, 1976
Resonant states in neural models match parametric properties of psychological data about conscious percepts

Growing neurophysiological support for predicted connections between:

- Consciousness
- Learning
- Expectation
- Attention
- Resonance
- Synchrony

e.g., experiments by J. Bullier, E. Miller, R. Desimone, C. Gilbert, V. Lamme, J. Reynolds, P. Roelfsema, W. Singer, N. Suga, etc.
ART
How we balance between expected and unexpected events

Interactions between COMPLEMENTARY SYSTEMS

Attentional System ↔ Orienting System

Expected Events ↔ Unexpected Events
Familiar Events ↔ Unfamiliar Events
Resonance ↔ Reset
Attention ↔ Memory Search
Learning ↔ Hypothesis Testing
Recognition

Temporal cortex  Prefrontal cortex  Hippocampal system  Nonspecific thalamus
ART 1 MODEL

ATTENTIONAL SYSTEM

ORIENTING SYSTEM

STM $F_2$

STM $F_1$

Nonspecific inhibitory gain control

Matching criterion: vigilance parameter

Reset and Search

Carpenter and Grossberg (1987)

INPUT

SG/WCCI/20
ART HYPOTHESIS TESTING AND LEARNING CYCLE

Choose category, or symbolic representation

Mismatch
Reset:
Novelty-
Sensitive
Arousal
Burst

Test hypothesis:
ART matching rule

How big a mismatch causes reset?

Choose another category

SG/WCCI/20
COGNITIVE LEARNING AND MEMORY CONSOLIDATION CYCLE

A dynamic cycle of
RESONANCE
and
RESET

As categories are learned, search automatically disengages
Modulatory novelty potentials subside as this type of memory consolidation ends
Direct access to globally best-matching category
Mathematical proof in: Carpenter & Grossberg, *CVGIP*, 1987
Many supportive psychological and neurobiological data

Explains how we can quickly recognize familiar objects even if, as we get older, we store enormous numbers of memories
ERP SUPPORT FOR HYPOTHESIS TESTING CYCLE

Event-Related Potentials: Human Scalp Potentials

ART predicted correlated sequences of P120-N200-P300

Event Related Potentials during oddball learning

P120 - mismatch; N200 - arousal/novelty; P300 - STM reset

Confirmed in: Banquet and Grossberg, 1987

[Diagram showing P120, N200, P300 with labels mismatch, arousal, STM reset]
Cells in inferotemporal cortex are actively reset during working memory tasks.

There is an 
“active matching process that was reset between trials.”
Miller, Li, Desimone, 1991
NEUROPHYSIOLOGICAL SUPPORT FOR HYPOTHESIS TESTING CYCLE

Classical data about hippocampus mismatch dynamics:
  Novelty potentials subside as learning proceeds
  e.g., Deadwyler et al., 1979, 1981; Otto and Eichenbaum, 1992;
  Sokolov, 1968; Vinogradova, 1975

More recent data from prefrenteal cortex (PFC) and hippocampus (HPC) when
monkeys learn object-pair associations:

  "Rapid object associative learning may occur in PFC, while HPC may guide
  neocortical plasticity by signaling success or failure…"
  Brincat and Miller, 2015
FROM CONCRETE TO ABSTRACT:
TASK-SENSITIVE VIGILANCE CONTROL

*Pay Attention!!!*
How do our cognitive categories learn
from our uniquely different experiences?

How do our brains learn CONCRETE knowledge for some
tasks and ABSTRACT knowledge for others?

Bridging between DISTRIBUTED PATTERN and SYMBOL

High Vigilance – Narrow Categories; CONCRETE
Mom’s face

Low Vigilance – Broad Categories; ABSTRACT
A face
VIGILANCE DATA IN INFEROTEMPORAL CORTEX

RECEPTIVE FIELD SELECTIVITY MUST BE LEARNED

Some cells respond selectively to particular views of particular faces
Other cells respond to broader features of an animal’s environment

Desimone, Gross, Perrett, …

EASY vs. DIFFICULT DISCRIMINATIONS: VIGILANCE!

“In the difficult condition the animals adopted a stricter internal criterion for discriminating matching from non-matching stimuli… The animal’s internal representations of the stimuli were better separated … increased effort appeared to cause enhancement of the responses and sharpened selectivity for attended stimuli…”

Spitzer, Desimone, and Moran, 1988
VIGILANCE CONTROL

\[ \rho \left| I \right| - \left| X \right| \leq 0 \quad \rho \leq \frac{X}{|I|} \] resonate and learn

\[ \rho \left| I \right| - \left| X \right| > 0 \quad \rho > \frac{X}{|I|} \] reset and search

\( \rho \) is a sensitivity or gain parameter
MINIMAX LEARNING PRINCIPLE

How to conjointly minimize predictive error and maximize generalization using error feedback in an incremental fast learning context in response to nonstationary data?
MATCH TRACKING realizes MINIMAX LEARNING PRINCIPLE

Given a predictive error, vigilance increases just enough to trigger search and thus sacrifices the minimum generalization to correct the error.

…and enables expert knowledge to be incrementally learned.
Are ART mechanisms realized within LAMINAR cortical and thalamic circuits?

YES!

SMART model
Synchronous Matching ART
Grossberg and Versace, 2008

MAIN QUESTIONS:
How are multiple levels of brain organization
spikes
local field potentials
inter-areal synchronous oscillations
spike-timing dependent plasticity
coordinated to
regulate stable category learning and attention
during cognitive information processing via
laminar cortical circuits
specific and nonspecific thalamic nuclei?
### THE MODEL FUNCTIONALLY EXPLAINS LOTS OF ANATOMICAL DATA

<table>
<thead>
<tr>
<th>Connections</th>
<th>Type</th>
<th>Functional interpretation</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>thalamic core A □ 4 A</td>
<td>D</td>
<td>Primary thalamic relay cells drive layer 4.</td>
<td>Blasdel and Lund (1983)</td>
</tr>
<tr>
<td>thalamic core A □ 6i A</td>
<td>D</td>
<td>Primary thalamic relay cells prime layer 4 via the 6 □ 4 modulatory circuit.</td>
<td>Blasdel and Lund (1983) for LGN □ 6; Callaway (1998) LGN input to 6 is weak and Layer 5 projections to 6 [Note 1]</td>
</tr>
<tr>
<td>thalamic core A □ RE A</td>
<td>D</td>
<td>Recurrent inhibition to primary and secondary thalamic relay cells.</td>
<td>Sherman and Guillery (2001); Jones (2002)</td>
</tr>
<tr>
<td>RE A □ thalamic core A</td>
<td>I</td>
<td>Off-surround to primary and secondary thalamic relay cells, synchronization of thalamic relay cells.</td>
<td>Cox et al. (1997); Pinault and Deschenes (1998); Sherman and Guillery (2001)</td>
</tr>
<tr>
<td>RE A (B) □ RE B(A)</td>
<td>GJ</td>
<td>Synchronize RE and thalamic relay cells.</td>
<td>Landisman et al. (2002)</td>
</tr>
<tr>
<td>thalamic A □ nonspecific</td>
<td>I</td>
<td>Inhibition of nonspecific thalamic cells, participates in the reset mechanism.</td>
<td>Kolmac and Mitrofanis (1997); Van der Werf et al. (2002)</td>
</tr>
<tr>
<td>nonspecific thalamic A □ 5 A</td>
<td>M</td>
<td>To 5 through apical dendrites in 1, participates in the reset mechanism.</td>
<td>Van der Werf et al. (2002)</td>
</tr>
<tr>
<td>4 A □ 2/3 A</td>
<td>D</td>
<td>Feedforward driving output from 4 to 2/3.</td>
<td>Fitzpatrick at al. (1985); Callaway and Wiser (1996)</td>
</tr>
<tr>
<td>2/3 A □ 4 B</td>
<td>D</td>
<td>Feedforward output from Area A to Area B.</td>
<td>Van Essen et al. (1986)</td>
</tr>
<tr>
<td>2/3 A □ 6i B</td>
<td>D</td>
<td>Feedforward output from Area A to Area B.</td>
<td>Van Essen et al. (1986)</td>
</tr>
<tr>
<td>2/3 A □ 5 A</td>
<td>D</td>
<td>Conveys layer 2/3 output to layer 5.</td>
<td>Callaway and Wiser (1996)</td>
</tr>
<tr>
<td>2/3 A □ 6i A</td>
<td>D</td>
<td>Conveys layer 2/3 output to layer 6i.</td>
<td>Callaway (1998)</td>
</tr>
</tbody>
</table>
THE MODEL FUNCTIONALLY EXPLAINS LOTS OF ANATOMICAL DATA

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</thead>
<tbody>
<tr>
<td>5 A × thalamic core B</td>
<td>D</td>
<td>Feedforward connections from Area A to Area B through secondary thalamic relay neurons.</td>
<td>Rockland (1999); Sherman and Guillery (2001)</td>
</tr>
<tr>
<td>5 A × 6 A</td>
<td>D</td>
<td>Delivers feedback to the 6 × 4 circuit from higher cortical areas, sensed at the apical</td>
<td>Callaway (1998); Callaway and Wiser (1996),</td>
</tr>
<tr>
<td></td>
<td></td>
<td>dendrites of 5 branching in 1.</td>
<td>class B” cells [Note 2]</td>
</tr>
<tr>
<td>6 A × 4 A</td>
<td>M</td>
<td>On-center to 4. Mediated by habituative gates.</td>
<td>Stratford et al. (1996); Callaway (1998);</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Grossberg and Raizada (2003)</td>
</tr>
<tr>
<td>6 A × 4 int. A</td>
<td>D</td>
<td>Off-surround to 4.</td>
<td>McGuire et al. (1984); Ahmed et al., (1997);</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Callaway (1998)</td>
</tr>
<tr>
<td>6 B × thalamic Core A</td>
<td>M</td>
<td>On-center to primary thalamic relay cells.</td>
<td>Sillito et al. (1994); Callaway (1998);</td>
</tr>
<tr>
<td>6 B × RE A</td>
<td>D</td>
<td>Off-surround to primary thalamic relay cells mediated by thalamic RE.</td>
<td>Guillery and Harting (2003); Sherman and</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Guillery (2001)</td>
</tr>
<tr>
<td>6 B × 2/3, 2/3 inh., 5 A</td>
<td>M</td>
<td>Intercortical feedback from 6 B to 1 area A, where it synapses on 2/3 excitatory and</td>
<td>Rockland and Virga (1989); Rockland (1994);</td>
</tr>
<tr>
<td></td>
<td></td>
<td>inhibitory neurons, as well as 5 apical dendrites branching in 1.</td>
<td>Salin and Bullier (1995)</td>
</tr>
</tbody>
</table>

Abbreviations: inh. = inhibitory neurons; RE = reticular nucleus; A = primary (thalamic, cortical) loop; B = secondary (thalamic, cortical) loop; D = driving excitatory connections; M = modulatory connections; I = inhibitory connections; GJ = gap junctions; int. = inhibitory interneuron. [Note 1]: Callaway (1998) subdivides Layer 6 neurons in 3 classes: Class I: provide feedback to 4C, receive input from LGN, and project back to LGN; Class IIa: dendrites in 6, axons from 2/3, project back to 2/3 with modulatory connections; Class IIb: dendrites in 5, project exclusively to deep layers (5 & 6) and claustrum. In the model, these populations are clustered in 2 classes, layer 6I and 6II, which provide feedback to thalamic relay cells and layer 4, respectively. [Note 2]: Callaway (1998) subdivides Layer 5 neurons in 3 classes: Class A: dendrites in 5, axons from 2/3, project back to 2/3 with modulatory connections; Class B: dendrites in 5, axons from 2/3, project laterally to 5 and PULVINAR; Class C: dendrites in 1, project to superior colliculus. In the model, these differences are ignored, and it is assumed that the model layer 5 neuron receives input from 2/3 (Classes A and B), as well modulatory input from the nonspecific thalamic nuclei (Class C, apical dendrites in 1, and provide output to 6I and second-order thalamic nuclei. The inner, recurrent loop with 2/3 has also been ignored.
BRAIN OSCILLATIONS DURING MATCH/MISMATCH

(a) TD CORTICOTHALAMIC FEEDBACK increases SYNCHRONY  Sillito et al., 1994

(b) MATCH

Increases $\gamma$ oscillations

(c) MISMATCH

increases $\theta$, $\beta$ oscillations

DATA

SIMULATION

FB ON

FB OFF

FB ON

FB OFF

FB ON

FB OFF

FB ON

FB OFF

FB ON

FB OFF

FB ON

FB OFF

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FB OFF

FB ON

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BRAIN OSCILLATIONS DURING MATCH/MISMATCH

DATA

(a) TD CORTICOTHALAMIC FEEDBACK increases SYNCHRONY

Sillito et al., 1994

(b) MATCH

Increases γ oscillations

V1 Buffalo et al., 2011
van Kerkoerle et al., 2014

V4 Buschman and Miller, 2009

Hippocampus Berke et al., 2009

(c) MISMATCH

increases θ, β oscillations

FB ON FB OFF

FB ON FB OFF

FB ON FB OFF

SIMULATION
VIGILANCE CONTROL: MISMATCH-MEDIATED ACETYLCHOLINE RELEASE

Acetylcholine (Ach) regulation by NONSPECIFIC THALAMIC NUCLEI via NUCLEUS BASALIS OF MEYNERT reduces AHP in layer 5

Ach thereby facilitates RESET (compare ART VIGILANCE control)

HIGH Vigilance ~ Sharp Code
LOW Vigilance ~ Coarse Code

CHOLINERGIC DENSITY AXONS IN V1 AND HOMOLOGS
Gu (2003)
If ACh dynamics collapse, then:

New category learning is undermined

Cortical layers
cannot resonate to recognize incoming information
and, in the limit,
cannot become conscious
WHAT DOES VIGILANCE HAVE TO DO WITH SLEEP

Fast rhythms (20-60 Hz) occur during awake states, accompanied by increased release of ACh in thalamus and cerebral cortex. Also occur during depolarizing phases of slow oscillation (0.5-1 Hz) in non-REM (NREM) sleep.

Steriade, 2004

NREM sleep has a cortical origin and multiple functions; e.g., metabolic clearance, memory consolidation. 


Stimulation of nucleus basalis elicits EEG activation and behavioral arousal from slow oscillations during sleep to fast oscillations during waking via ACh actions on layer 5 pyramidal neurons.

Metherate, Coex, and Ashe, 1992

Loss of basal forebrain ACh neurons contributes to sleep disruption and cognitive deficits. 

Kalinchuk et al., 2015; Nair et al., 2016; Vazaquez and Beghdoyan, 2001
SLEEP, UP AND DOWN STATES, AND ACh

Slow wave generation in layer 5 synchronizes activity across neocortex
Ball et al., 1977; Calvet et al, 1973; Chagnac-Amitai and Connors, 1989

UP and DOWN states occur during slow wave sleep
All cells, excitatory and inhibitory, shut off during the DOWN state
including cells that generated silencing discharge
Layer 5 cells initiate this activity cycle
Fast-spiking inhibitory interneurons have an early onset
Steriade and Timofeev, 2003; Steriade et al., 1993; Volgushev et al., 2006
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HOW ARE UP AND DOWN STATES CAUSED?
SLEEP, UP AND DOWN STATES, AND ACh

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Steriade and Timofeev, 2003; Steriade et al., 1993; Volgushev et al., 2006

HOW ARE UP AND DOWN STATES CAUSED?

An emergent property of LAMINART cortical model!
Grossberg, 1999; Grossberg and Raizada, 2000;...

Helps to explain both waking and sleep dynamics!
SLEEP, UP AND DOWN STATES, AND ACh

Here is the circuit:

Uses its properties of
Balanced excitation and inhibition
Contrast normalization
RELATES SLEEP DISORDERS IN ALZHEIMER’S & AUTISM to problems with ACh-mediated VIGILANCE CONTROL in layer 5
RELATES SLEEP DISORDERS IN ALZHEIMER’S & AUTISM
to problems with ACh-mediated VIGILANCE CONTROL in layer 5

A VICIOUS CYCLE

β-amyloid peptide concentration increases due to sleep deprivation, leading to more plaque formation
Ju et al., 2013, 2014, 2017; Spira et al., 2013

More plaques in layer 5 can disrupt ACh-mediated UP and DOWN sleep states, thereby further disrupting sleep
WHAT DOES VIGILANCE HAVE TO DO WITH AUTISM?

Prediction that many individuals with autism have TONIC vigilance stuck at high values

Leads to
Hyperconcrete categorization and recognition
Narrow focus of attention

Grossberg and Seidman, 2006, Psychological Review, 113, 483-525.

Supportive psychophysical data from high-functioning autistic individuals

Neuron pathology, morphological abnormalities, and abnormalities of ACh dynamics
in cerebral cortex and nucleus basalis of autistic individuals
Perry et al. (2001). American Journal of Psychiatry, 158, 1058-1066
NOT THE ONLY PROBLEM DURING AUTISM

multiple genes are affected

cf. Grossberg and Seidman, 2006; Grossberg and Kishan, 2018

---

Diagram:

- Basal ganglia
  - Incorrect gate opening/closing
  - Neocortex
    - Hypofrontal blocking fails
    - No Theory of Mind
    - Hyperspecific learning
  - Hippocampus
    - Adaptive timing fails
  - Amygdala
    - Emotionally depressed
  - Cerebellum
HOW DO WE CONSCIOUSLY SEE?
and
HOW DOES A BREAKDOWN IN THIS PROCESS LEAD TO VISUAL NEGLECT?
HOW DO WE CONSCIOUSLY SEE?
and
HOW DOES A BREAKDOWN IN THIS PROCESS LEAD TO VISUAL NEGLECT?


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HOW DO WE CONSCIOUSLY SEE?
and
HOW DOES A BREAKDOWN IN THIS PROCESS LEAD TO VISUAL NEGLECT?


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...very briefly...
What is the Hard Problem of Consciousness?

Wikipedia

“…is the problem of explaining how and why we have qualia or phenomenal experiences…”

Chalmers (1995):

“The really hard problem of consciousness is the problem of experience. When we think and perceive, there is a whir of information-processing, but there is also a subjective aspect…”
What is the Hard Problem of Consciousness?

Internet Encyclopedia of Philosophy

“The hard problem of consciousness is the problem of explaining why any physical state is conscious rather than unconscious… It is the problem of explaining why…conscious mental states “light up” and directly appear to the subject…. we can still meaningfully ask the question, Why is it conscious?...”
Before jumping in, it is fair to ask:
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What kind of event occurs in the brain that is anything more than a “whir of information processing”

What happens when conscious mental states “light up” and directly appear to a subject?
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Our brains sometimes go into a context-sensitive RESONANT STATE that can involve multiple brain regions
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Our brains sometimes go into a context-sensitive RESONANT STATE that can involve multiple brain regions

ALL CONSCIOUS STATES ARE RESONANT STATES
Before jumping in, it is fair to ask:

What kind of event occurs in the brain that is anything more than a “whir of information processing”

What happens when conscious mental states “light up” and directly appear to a subject?

Our brains sometimes go into a context-sensitive RESONANT STATE that can involve multiple brain regions

ALL CONSCIOUS STATES ARE RESONANT STATES

Not all brain dynamics are resonant, so consciousness is not just a “whir of information processing”
WHAT IS A RESONANT BRAIN STATE?

A dynamical state during which neuronal firings across a brain network are amplified and synchronized when they interact via reciprocal excitatory feedback signals during a matching process that occurs between bottom-up and top-down pathways.
CENTRAL CLAIM

Conscious states are part of larger adaptive behavioral capabilities that help us to adapt to a changing world.

Resonances for conscious

seeing help to ensure effective reaching

hearing help to ensure effective speaking

feeling help to ensure effective goal-oriented action
CENTRAL CLAIM

Conscious states are part of larger adaptive behavioral capabilities that help us to adapt to a changing world.

Resonances for conscious:
- Seeing help to ensure effective reaching
- Hearing help to ensure effective speaking
- Feeling help to ensure effective goal-oriented action
WHY DID EVOLUTION INVENT CONSCIOUSNESS?

Visual inputs to the retina are ambiguous, noisy, and incomplete
BLIND SPOT AND RETINAL VEINS
another reason for boundary completion and surface filling-in

Kolb, Fernandez & Anderson
http://retina.umh.es/Webvision/sretina.html
TOP-DOWN VIEW OF THE RETINA

Blind spot, retinal veins, and layers all interfere
VISUAL IMAGES ARE OCCLUDED BY THE BLIND SPOT AND RETINAL VEINS

The pattern formed on a retina by a dark line

...is not even connected!

HOW COULD YOU REACH TO THE LINE HERE?
WHY DID EVOLUTION INVENT CONSCIOUSNESS?

Visual inputs to the retina are ambiguous, noisy, and incomplete

Multiple processing stages are needed to generate a sufficiently complete and stable surface representation that can control effective looking and reaching

Hierarchical Resolution of Uncertainty
WHY DON’T WE **SEE** BLIND SPOT AND RETINAL VEINS?!

*The pattern formed on a retina by a dark line*

...is not even *connected*!

Eye jiggles in its orbit
Stabilized images fade
EVERY LINE IS AN ILLUSION!

**Boundary completion and grouping**

Which boundaries to connect?

**Surface filling-in**

What colors and brightnesses do we *SEE*?
WHAT DO WE CALL AN ILLUSION?

...an unexpected combination of boundary completion and surface filling-in
WHY DID EVOLUTION INVENT CONSCIOUSNESS?

Visual inputs to the retina are ambiguous, noisy, and incomplete.

Multiple processing stages are needed to generate a sufficiently complete and stable surface representation that can control effective looking and reaching.

This surface representation is predicted to occur in V4.

A SURFACE-SHROUD RESONANCE between V4 and PPC

“lights up” the V4 surface representation with an extra degree of freedom.

CONSCIOUS AWARENESS!

and uses IT to control LOOKING at and REACHING to unoccluded surface regions.
WHY ARE MULTIPLE PROCESSING STAGES NEEDED TO COMPUTE A GOOD ENOUGH REPRESENTATION WITH WHICH TO CONTROL MOVEMENTS?

Because of the way that our brains compute

COMPLEMENTARY COMPUTING
Boundaries and Surfaces are complementary

HIERARCHICAL RESOLUTION OF UNCERTAINTY
e.g., boundary completion

Visual consciousness “lights up” surface representations that can safely be used to look and reach
WHY DID EVOLUTION INVENT CONSCIOUSNESS?

The SURFACE-SHROUD RESONANCE between V4 and PPC can also propagate TOP-DOWN to V2 and V1 and resonate with representations that are consistent with the V4 surface representation and suppress those that are not using the ART Matching Rule for top-down attention only data consistent with the action are selected and also BOTTOM-UP to prefrontal cortex
PREDICTIONS

ALL CONSCIOUS STATES ARE RESONANT STATES
Grossberg (1976)

VISIBLE QUALIA ARE SURFACE PERCEPTS
Grossberg (1984)
PREDICTIONS

ALL CONSCIOUS STATES ARE RESONANT STATES
Grossberg (1976)

VISIBLE QUALIA ARE SURFACE PERCEPTS
Grossberg (1984)

WHAT KIND OF RESONANCE SUPPORTS VISIBLE SURFACE QUALIA?
How do we see?!
PREDICTIONS

ALL CONSCIOUS STATES ARE RESONANT STATES
Grossberg (1976)

VISIBLE QUALIA ARE SURFACE PERCEPTS
Grossberg (1984)

WHAT KIND OF RESONANCE SUPPORTS VISIBLE SURFACE QUALIA?
How do we see?!

A SURFACE-SHROUD RESONANCE
Grossberg (2009+)
## CLASSIFICATION OF RESONANCES

<table>
<thead>
<tr>
<th>Type of Resonance</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface-shroud resonances</td>
<td>Support conscious seeing of visual qualia</td>
</tr>
<tr>
<td>Feature-category resonances</td>
<td>Support conscious recognition of visual objects and scenes</td>
</tr>
<tr>
<td>Stream-shroud resonances</td>
<td>Support conscious hearing of auditory qualia</td>
</tr>
<tr>
<td>Spectral-pitch-and-timbre resonances</td>
<td>Support conscious recognition of sources in auditory streams</td>
</tr>
<tr>
<td>Item-list resonances</td>
<td>Support conscious recognition of speech and language</td>
</tr>
<tr>
<td>Cognitive-emotional resonances</td>
<td>Support conscious feelings and recognition of them</td>
</tr>
</tbody>
</table>
WHAT IS A SURFACE-SHROUD RESONANCE?
WHAT IS AN ATTENTIONAL SHROUD?

Surface-fitting spatial attention

ATTENTIONAL SHROUD!

marks the object-hood of the as-yet-undefined object category

Tyler and Kontsevich (1995) used shrouds to study perceptual transparency

Cf. Cavanagh, Pylyshyn, Yantis,…

PREDICTION:
Shrouds enable learning of invariant object categories
Not explained in this talk, but see:

Fazl, Grossberg, and Mingolla (2009)
Cao, Grossberg, and Mingolla (2011)
Grossberg, Markowitz, and Cao (2011)
Foley, Grossberg, and Mingolla (2012)
Chang, Grossberg, and Cao (2014)
BOTTOM-UP SPATIAL ATTENTIONAL COMPETITION

Spatial Attention

Competition

Perceptual Surfaces

More luminous

Less luminous
SURFACE-SHROUD RESONANCE

Spatial Attention

Competition

Perceptual Surfaces

Neurophysiology: Reynolds and Desimone (2003)
SURFACE-SHROUD RESONANCE

An active SURFACE-SHROUD RESONANCE means that sustained SPATIAL ATTENTION IS FOCUSED ON THE OBJECT SURFACE
SURFACE-SHROUD RESONANCE

An active SURFACE-SHROUD RESONANCE means that sustained SPATIAL ATTENTION IS FOCUSED ON THE OBJECT SURFACE

A SURFACE-SHROUD RESONANCE ALSO SUPPORTS CONSCIOUS SEEING OF AN ATTENDED OBJECT
SURFACE-SHROUD RESONANCE

An active SURFACE-SHROUD RESONANCE means that sustained SPATIAL ATTENTION IS FOCUSED ON THE OBJECT SURFACE

A SURFACE-SHROUD RESONANCE ALSO SUPPORTS CONSCIOUS SEEING OF AN ATTENDED OBJECT

WHY SHOULD YOU BELIEVE THIS?
FACADE AND 3D LAMINART simulations explain a lot of psychophysical and neurobiological data with these model hypotheses

e.g., psychophysics, anatomy, and neurophysiology about:
random-dot stereograms Fang and Grossberg (2009)
3D neon and transparency Grossberg and Yazdanbakhsh (2005)
texture segregation Bhatt, Carpenter, and Grossberg (2007)
McCullough effect Grossberg, Hwang, and Mingolla (2002)
3D shape-from-texture Grossberg, Kuhlmann, and Mingolla (2007)
Bregman-Kanizsa figure-ground separation, Kanizsa stratification, Munker-White, Benary cross, and checkerboard percepts Kelly and Grossberg (2000)
watercolor illusion Pinna and Grossberg (2005)
border ownership, stereoscopic cues, and Gestalt grouping rules Grossberg (2016)
They are consistent with many neurophysiological experiments about V2 and V4

e.g., V2:
O’Herron and von der Heydt (2009)
Ziu, Sugihara, and von der Heydt (2007)
Qiu and von der Heydt (2005)
Von der Heydt, Zhou, and Friedman (2000)
Zhang and von der Heydt (2010)
Zhou, Friedman, and von der Heydt (2000)

V4:
Chelazzi, Miller, Duncan, and Desimone (2001)
Desimone and Schein (1987)
Lueck et al. (1989)
Ogawa and Komatsu (2004)
Reynolds, Pasternak, and Desimone (2000)
Schiller and Lee (1991)
Zeki (1983)

NEED MORE FOCUSED EXPERIMENTS!
Explaining clinical data about consciousness with Surface-Shroud Resonances

PARIETAL VISUAL NEGLECT
No parietal cortex, no Surface-Shroud Resonance!

Classical Review of effects of lesions in inferior parietal lobule (IPL)
Driver and Mattingly (1989)

Head-centered shroud coexists with retinotopic surface qualia
Shown by how neglect varies with patient’s direction of gaze
Kooistra and Heilman (1989)

Competition for spatial attention across parietal cortex
Shown by how neglect varies with isolated vs. simultaneous cues

Preserved figure-ground segmentation during neglect
Shown by how grouping can overcome neglect
Mattingley, Davis, and Driver (1997)
Explaining clinical data about consciousness with Surface-Shroud Resonances

PARIETAL VISUAL NEGLECT
Unconscious processing of neglected object identity: seeing vs. knowing
Shown by Implicit knowledge of neglected stimuli (color, shape, identity, …)

Mattingley, Bradshaw, and Bradshaw (1995)
McGlinchey-Berroth et al. (1993)
WHAT KINDS OF RESONANCES SUPPORT KNOWING VS. SEEING?

**What Stream**

- **IT**
- **V2/4**

**Where Stream**

- **PPC**

**KNOWING**
- Feature-Category Resonance

**SEEING**
- Surface-Shroud Resonance

Synchronous linkage between resonances enables us to KNOW what the object is as we SEE it.
Explaining data about consciousness with Surface-Shroud Resonances

PARIETAL VISUAL NEGLECT
A link between visual neglect and motor planning deficits: “seeing to reach”
Shown by abnormal motor biases
  Heilman et al. (1985)
  Mattingley et al. (1998)

IPL lesions lead to deficits in sustained visual attention:
  no Surface-Shroud Resonance to maintain attention
  Rueckert and Grafman (1998)
WHAT KINDS OF RESONANCES SUPPORT KNOWING VS. SEEING?

WHAT STREAM

KNOWING
Feature-Category Resonance

SEEING
Surface-Shroud Resonance

WHERE STREAM

V2/4

VISUAL AGNOSIA: reaching without knowing

Patient DF  Goodale et al, 1991
WHAT KINDS OF RESONANCES SUPPORT KNOWING VS. SEEING?

What Stream

Where Stream

KNOWING
Feature-Category Resonance

SEEING
Surface-Shroud Resonance

VISUAL AGNOSIA: reaching without knowing
Patient DF  Goodale et al, 1991

Attention and Intention both parietal cortical functions
Andersen, Essick, and Siegel, 1985; Gnadt and Andersen, 1988; Snyder, Batista, and Andersen, 1997, 1998
Brain dynamics of normal and abnormal learning, cognition, and consciousness with applications to Alzheimer’s disease, autism, amnesia, sleep, neglect, and memory consolidation.

The key role of BRAIN RESONANCES in conscious seeing and recognition notably of Adaptive Resonance Theory hypothesis testing and category learning dynamics in LAMINAR CORTICAL CIRCUITS in response to properly pre-processed perceptual data.

Lots more to do, including roles of basal ganglia and prefrontal cortex…
ART CURRENTLY HAS AN UNRIVALLED RANGE

“The gift that keeps on giving”

It has explained and predicted much more data than competing cognitive and neural theories

That range extends to helping to provide emerging neural explanations of mental disorder symptoms that afflict millions of people

Alzheimer’s disease
Autism
Fragile X syndrome
ADHD
Schizophrenia
Sleep disorders

and how brain lesions cause problems with

Medial temporal amnesia
Memory consolidation
Visual and auditory neglect

I hope some of you will help to advance this theory in either its biological or technological incarnations!