Self-Organization:

Production of organized patterns, resulting from localized interactions within the components of the system, without any central control

C. Anderson, G. Theraulaz, and J.-L. Deneubourg,
Self-assemblages in insect societies. Insectes soc. 49 (2002) 99–110

https://www.youtube.com/watch?v=cIgHEhziUxU

Self-Organizing Behaviors We'll Sample

- Flocking and Schooling
- Synchronization
- Foraging
- Task Allocation

Flocking: http://www.youtube.com/watch?v=nffdc9sLYnY

Schooling: http://www.youtube.com/watch?v=-Udq_41X6Xs

No leader or global information required!

Why Flock or School?

Some hypotheses

- Predators will think that flock or school is single (large, threatening) organism
- Predators won’t be able to target individuals in the flock or school
- The flock or school will be more efficient at catching prey (via cooperative hunting) than individuals alone
- The flock or school will increase the individuals’ aero/hydro-dynamic efficiency (like a peloton in bicycling)

Many hypotheses! Possibly all are correct.

How to Flock or School (without a leader, with only local information)?

"Boids" model, Craig Reynolds, 1987

Craig Reyonlds

Computer Graphics, Volume 21, Number 4, July 1987

Flocks, Herds, and Schools: A Distributed Behavioral Model

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Abstract

The aggregate motion of a flock of birds, a herd of land animals, or a school of fish is a beautiful and familiar part of the natural world. But this type of complex motion is rarely seen in computer animation. This paper explores an approach based on simulation as an alternative to scripting the paths of each bird individually. The simulated flock is an elaboration of a particle system, with the simulated birds being the particles. The aggregate motion of the simulated flock is created by a distributed behavioral model much like that at work in a natural flock; the birds choose their own course. Each simulated bird is implemented as an independent actor that navigates according to its local perception of the dynamic environment, the laws of simulated physics that rule its motion, and a set of behaviors programmed into it by the "animator." The aggregate motion of the simulated flock is the result of the dense interaction of the relatively simple behaviors of the individual simulated birds.

it seems randomly arrayed and yet is magnificently synchronized. Perhaps most puzzling is the strong impression of intentional, centralized control. Yet all evidence indicates that flock motion must be merely the aggregate result of the actions of individual animals, each acting solely on the basis of its own local perception of the world.

One area of interest within computer animation is the description and control of all types of motion. Computer animators seek both to invent wholly new types of abstract motion and to duplicate (or make variations on) the motions found in the real world. At first glance, producing an animated, computer graphic portrayal of a flock of birds presents significant difficulties. Scripting the path of a large number of individual objects using traditional computer animation techniques would be tedious. Given the complex paths that birds follow, it is doubtful this specification could be made without error. Even if a reasonable number of suitable paths could be described, it

Boids rules of flocking (or schooling), in order of relative importance:

1. **Collision Avoidance:** avoid collisions with nearby flockmates

2. **Velocity Matching:** attempt to match velocity with nearby flockmates

3. **Flock Centering:** attempt to stay close to nearby flockmates

Example Boids Simulation of Fish Schooling

http://www.youtube.com/watch?v=hWcOTLtnm0Y

Netlogo Flocking Model
(in Models Library→ Biology)

Rules for each bird:

If I'm too close to nearest neighbor, **separate**

> **Separate:** turn 90 degrees from nearest-neighbor's heading, or *max-separate-turn*, whichever is less

Otherwise: **align** and **cohere**

> **Align:** Turn so my heading is the same as the average heading of my neighbors (or turn max-align-turn, whichever is less)

> **Cohere:** Turn so I will move closer to my neighbors (or max-cohere-turn, whichever is less).

These rules affect each bird's heading direction. Each bird always moves forward at same constant speed

Examples of Synchronization in Nature

- Fireflies flashing (only occurs in specific species)
- Crickets chirping
- Cicadas development and emergence
- Neurons firing
- Heart cells beating
- Women’s menstrual cycles

Why Synchronize?

Again, multiple hypotheses!

- Makes males' location more visible to females
- Makes small groups of males appear larger, more attractive to females
- Reduces "noise": males can more easily spot females in the dark between flashes

Perhaps all of these are correct...

How to synchronize?

Assumptions:

No leader.

Each individual firefly only sees neighbors flashes.

Each firefly is a natural "oscillator", with a natural flashing frequency of about 1 second.

Excitation builds up in neurons, reaches threshold, leading to flash.

However, if the firefly sees flash from a neighbor, this either resets its cycle (excitation set to 0) or speeds up its cycle.

Result of interacting group: synchrony! (via "coupled oscillators")

Netlogo Fireflies Model
(in Models Library→ Biology)

- Each firefly cycles through its own clock, flashing at beginning of each cycle, then resetting clock to zero once it reaches the maximum.

- All fireflies have the same cycle length.

- Upon *setup*, all fireflies begin at a random point in their cycles.

- As fireflies perceive other flashes near them (within radius of one patch), they use this information to reset their own clocks.

- The fireflies have a parameter, *flash-length*, which is the duration, in ticks, of each flash.

- The fireflies have a parameter, *flashes-to-reset*, which gives the number of flashing fireflies a firefly has to see in its vision radius in order to reset its clock.

- The fireflies can use one of two rules:
  - **Phase Delay:**

    If I saw enough flashes in my vision radius, I reset my clock to *flash-length*, as though I had just finished flashing. This will synchronize me with the flashes I saw.

  - **Phase Advance:**

    If I saw enough flashes in my vision radius, I will reset my clock to zero, which causes me to flash immediately.

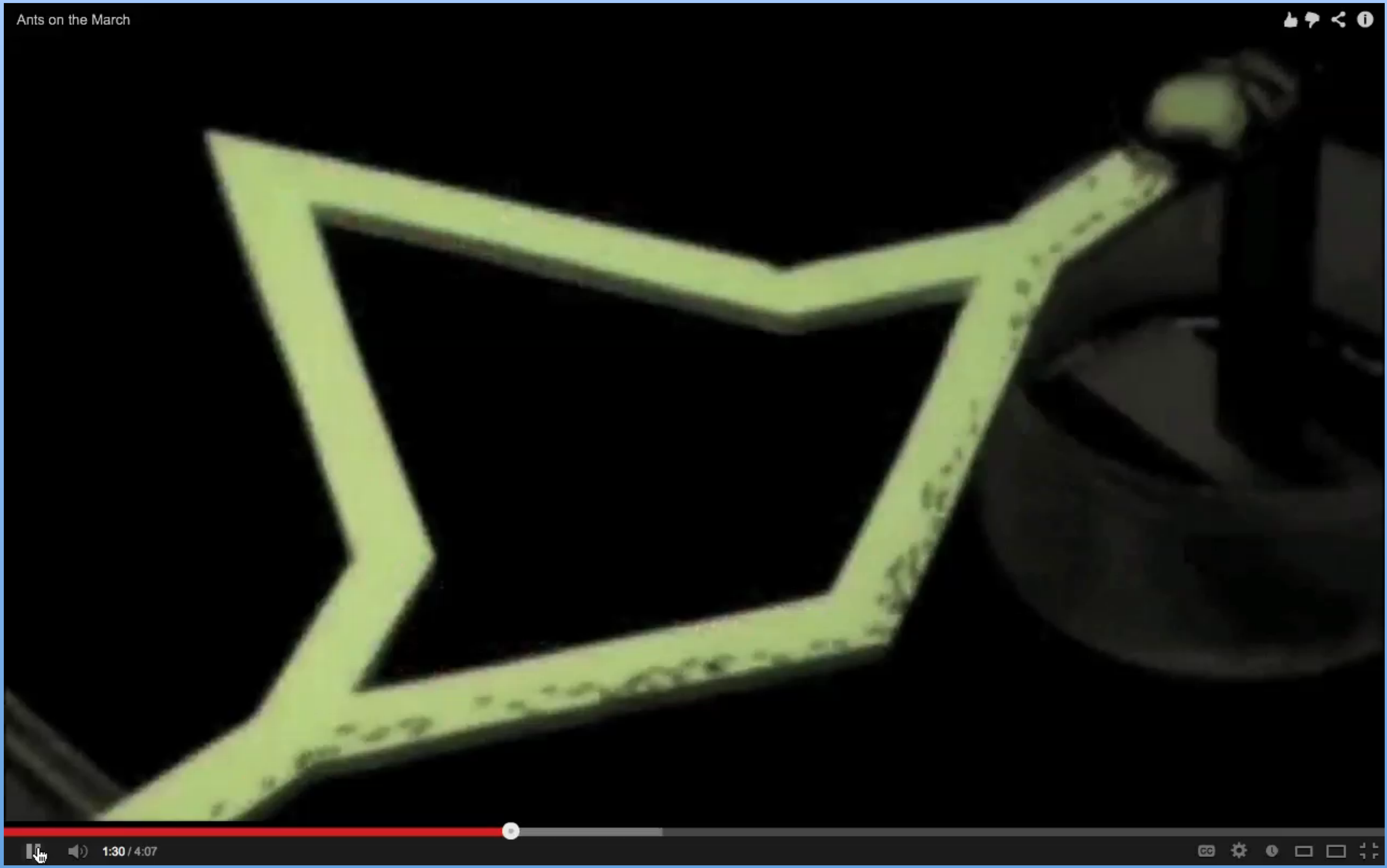
http://www.newerapestcontrol.com/web/wp-content/uploads/2012/09/trail-of-ants.jpeg

http://www.futurity.org/science-technology/%E2%80%98anternet%E2%80%99-algorithm-works-like-the-web/

http://upload.wikimedia.org/wikipedia/commons/thumb/3/3a/Ant_trail.jpg/220px-Ant_trail.jpg

Ant Foraging

- Ants move randomly in many different directions
- When an ant encounters a food source, it returns to the nest, leaving a pheromone trail.
- Ants encountering this trail are likely to follow it.
- In the absence of reinforcement, the pheromone will dissipate.



http://www.youtube.com/watch?v=qKufaBQWrJ0

- Ants model
- Does population increase matter when pheromone is on?

- At any given time, the existing trails and their strengths encode the colony’s collective information about its food environment

- This information adapts to changes in environmental conditions.

Task allocation in ant colonies

Interaction patterns and task allocation in ant colonies

Deborah M. Gordon

Summary

Social insect colonies must accomplish many tasks, such as foraging, tending brood, constructing a nest, and so on. Task allocation is the process that adjusts the numbers of workers engaged in each task. This chapter discusses how information from other individuals is used in task decisions, and in particular, how workers use the pattern of interactions they experience, rather than the content of messages received. Empirical studies of harvester ants led to a mathematical model of task allocation in which environmental stimuli and interaction patterns both influence an individual's task. I outline the main results from

Deborah Gordon

"Task allocation is the process that adjusts the number of workers engaged in each task in a way appropriate to the current situation. Task allocation operates without central or hierarchical control."

Task allocation in harvester ants (Gordon, 2002):

- Workers in a colony divide themselves among a number of tasks:
  - nest maintenance
  - patrolling
  - foraging
  - refuse sorting
  - etc.

http://www.confluence.org/fi/all/n61e027/pic1.jpg

http://alexwild.smugmug.com/Ants/Taxonomic-List-of-Ant-Genera/Myrmecocystus/i-qHNT5q5/1/M/navajo3-M.jpg

- The number of workers pursuing each kind of task adapts to changes in the environment – e.g., weather, food availability, threats.

- E.g., if nest is disturbed, number of nest-maintenance workers will increase, and number of foragers decrease.

- Or if food supply is large and high-quality, number of foragers will increase.

- In short, individuals can choose tasks, according to what tasks need the most attention, and how many other ants are already doing these tasks!

Question:

- How does an individual ant decide which task to adopt in response to nest-wide environmental conditions, even though no ant directs the decision of any other ant, and each ant interacts only with a small number of other ants?

Answer (Gordon, 2002):

Ants decide to adopt particular tasks as a function of:

1. What they encounter in the environment

2. Their rate of interaction with ants performing different tasks.

An ant can tell what job another ant has been doing by sensing chemical residues on the other ant.

Forager interaction (Deborah Gordon, filming with videoscope inside the nest)

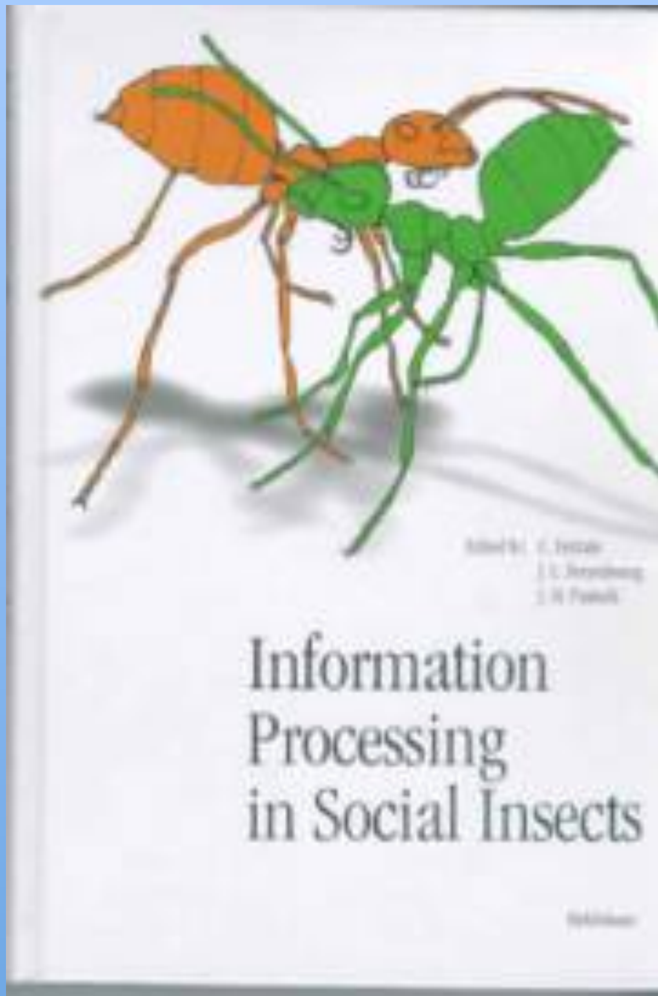
http://www.youtube.com/watch?v=oYb044RvA0w

Puzzle

- Gordon and colleagues observed that larger colonies are more deterministic and consistent in task allocation than smaller colonies.
- Why? Pause the video and think about it for a bit.
- **Hypothesis:** ants in larger colonies can get better statistics on interaction rates!

Information processing as a unifying framework for understanding self-organization

Do self-organizing systems process information?



ENTOMOLOGY

Getting the Behavior of Social Insects to Compute

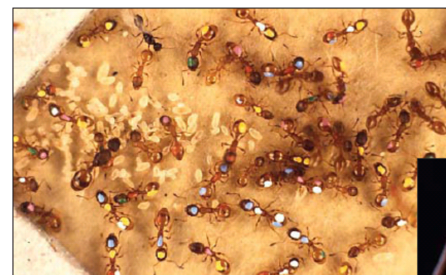
By envisioning ant colonies as computer networks, entomologists have begun to unravel complex behavioral patterns

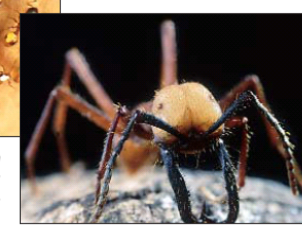
CAMBRIDGE, U.K.—In a recent AT&T commercial, blue ants scurry through a maze and across a chasm in pursuit of an unknown goal. Only when the cartoon "camera" zooms out does the bigger picture come into view: The streams of ant traffic are forming the familiar lines of AT&T's logo. These fictitious bugs are a tongue-in-cheek illustration of how global order can emerge from what appears to be local chaos—a concept that computer programmers have been cribbing from insect behavior for years to make networks run more efficiently. For example, in a routing program called Ant Colony Optimization, virtual ants lay pheromone trails to direct the flow of data packets without cumbersome central planning.

Now, reversing roles, a handful of entomologists are cribbing from the computer scientists. They deconstruct many behavioral patterns of social insects and show how these operate much like computer algorithms. "It's not a superficial resemblance," says Tom Seeley, who studies bee communication at Cornell University in Ithaca, New York.

For decades, entomologists have known that insect colonies are capable of complex collective action, even though individuals adhere to straightforward routines. When foraging, for example, workers appear to march to a drumbeat that dictates when to turn and farthest from the nest, as foragers or soldiers. But Franks and Tofts reverse-engineered a colony and showed that this correlation arises from a simpler rule: Workers do the nearest available job and move outward when they are replaced, usually by a younger ant.

By thinking like computer programmers and scrutinizing the actions of individual



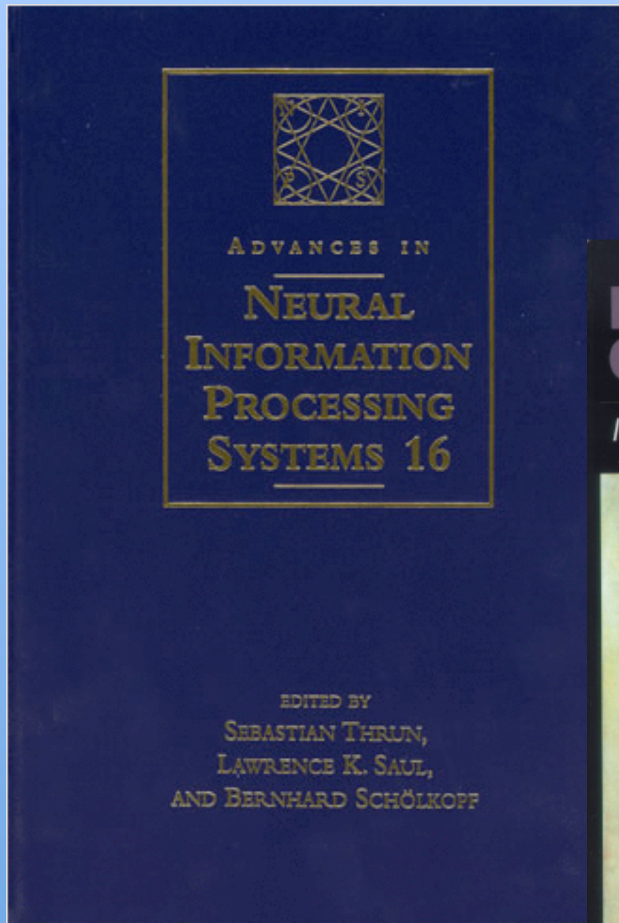


The original microchips. From the brutish *Eciton burchelli* (*right*) to the diminutive *Leptothorax albipennis* (*above*), ant problem solving resembles the inner workings of computer circuitry.

ants, scientists have revealed behavioral rules that govern group problem solving, just as assemblies of simple circuits can perform com-

slowly than premium sites. Rule two: Once an undetermined threshold number of workers are recruiting for the same site, the recruiters become movers, carrying the entire colony to its new digs. As a result, the colony always agrees on the best site, even if it is discovered later than other sites.

Also employing meticulous observations of individuals, Iain Couzin of the University of Leeds, U.K., has uncovered the laws of army ant traffic. Just as computer networks must maintain speed during high data flow, *Eciton burchelli* must avoid getting knocked off the trail or turned around during foraging expeditions known as "swarm raids." Up to 200,000 foragers moving in opposite directions must follow the same pheromone trail, so the risk of gridlock is high. At the "Mathematics of Social Insects" meeting in Cambridge, U.K., last December, Couzin and Franks reported that the flow of ants with two simple turning rules. Outbound workers turn aside sharply from encounters with ants moving in the opposite direction, while inbound workers, laden with food, turn aside more slowly. In computer simulations, these rules keep both streams in


ADVANCES IN
NEURAL INFORMATION PROCESSING SYSTEMS 16
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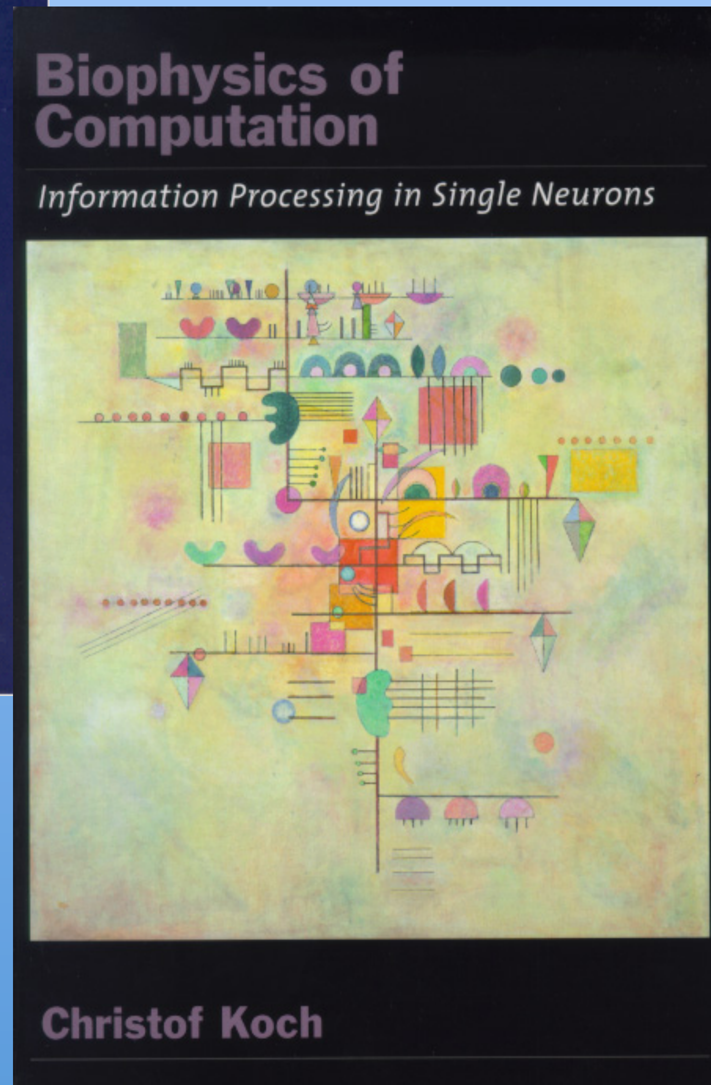
Biophysics of Computation
Information Processing in Single Neurons
Christof Koch

Learning from Bacteria about Natural Information Processing

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[b] *The Center for Theoretical and B*
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Under natural growth conditions
To conduct complex cooperative
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matic aspects. I describe how co
communication-based interplay b
ual cells assume newly co-genera
genetic information of the cells, t
responses to all environmental co
lems, they assess the problem via
experience, and then execute dist
ria in the colony—transforming t
examples of swarming intelligen

Information processing and signal integration in bacterial quorum sensing

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Abstract

Bacteria communicate using secreted chemical signaling molecules called autoinducers in a pro-

Immunology as Information Processing

Stephanie Forrest
Steven A. Hofmeyr

1 INTRODUCTION

This chapter describes the behavior of the
processing perspective. It reviews a seri
versity of New Mexico and the Santa Fe
explored the theme "immunology as in
cover the spectrum from serious modeli
such as crossreactive responses in anima

UNDERSTANDING INFORMATION PROCESSING IN THE IMMUNE SYSTEM; COMPUTER MODELING AND SIMULATIONS

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ABSTRACT

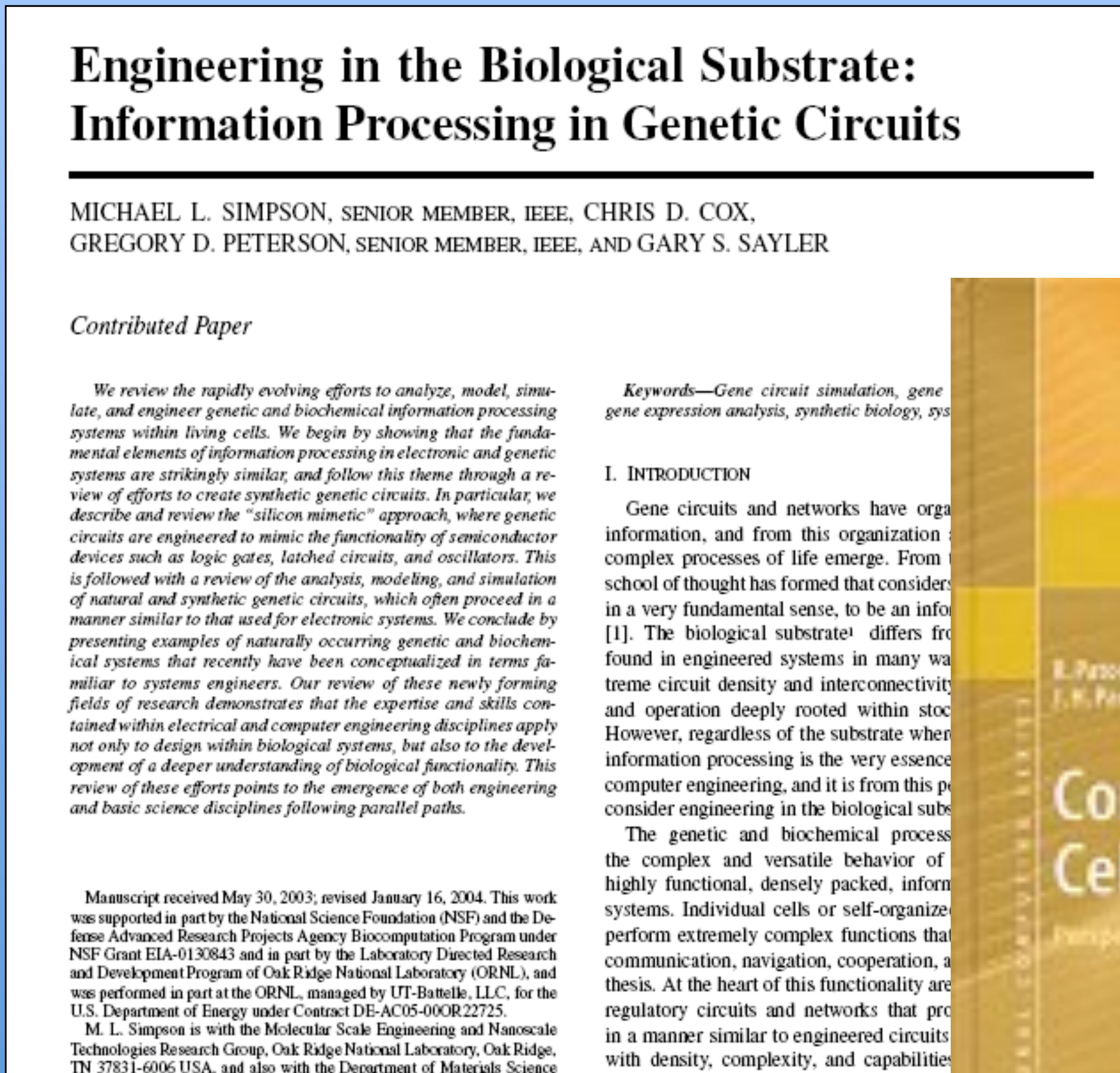
The immune system protects our organisms against pathogens and aberrant cells. It achieves this capability by processing and evaluating a wide variety of molecular signals many of which are generated by its own agents.

Even though the amount of experimental data describing single cellular mechanisms is rapidly growing a satisfactory understanding of the immune system's operations remains very difficult due to the complexity of the system.

Simmune, a novel computer program, allows to investigate cellular cooperation within the immune system through simulations on the level of interactions between individual cells. Such simulations may allow to bridge the scale gap between experimentally accessible low level data and higher level multicellular processes which determine the appropriate response to pathogen challenges.

2. SIGNALS OF DANGER OR HARM

Some modern concepts describe the IS as a signal processing system capable of recognizing sources of harm or even potential harm: danger [6]. The signals which the IS processes are molecular signals. They are received by the cells of the IS with the help of specialized receptors located in their cellular membranes. The signals can consist of molecular structures of pathogen surfaces or of molecules and molecule complexes secreted by, or presented on the surface of, other cells. Certain pathogen surface molecules may be regarded as danger signals the IS has 'learned' in the course of evolution and memorized in the germ line as genes coding for the receptors that specifically recognize (bind to) these molecules. The ligation of these receptors triggers intracellular signaling events that then lead to cellular responses like the secretion of signal molecules for other immune system cells or the activation of chemicals attacking the pathogens



Engineering in the Biological Substrate: Information Processing in Genetic Circuits

MICHAEL L. SIMPSON, SENIOR MEMBER, IEEE, CHRIS D. COX,
GREGORY D. PETERSON, SENIOR MEMBER, IEEE, AND GARY S. SAYLER

Contributed Paper

We review the rapidly evolving efforts to analyze, model, simulate, and engineer genetic and biochemical information processing systems within living cells. We begin by showing that the fundamental elements of information processing in electronic and genetic systems are strikingly similar, and follow this theme through a review of efforts to create synthetic genetic circuits. In particular, we describe and review the "silicon mimetic" approach, where genetic circuits are engineered to mimic the functionality of semiconductor devices such as logic gates, latched circuits, and oscillators. This is followed with a review of the analysis, modeling, and simulation of natural and synthetic genetic circuits, which often proceed in a manner similar to that used for electronic systems. We conclude by presenting examples of naturally occurring genetic and biochemical systems that recently have been conceptualized in terms familiar to systems engineers. Our review of these newly forming fields of research demonstrates that the expertise and skills contained within electrical and computer engineering disciplines apply not only to design within biological systems, but also to the development of a deeper understanding of biological functionality. This review of these efforts points to the emergence of both engineering and basic science disciplines following parallel paths.

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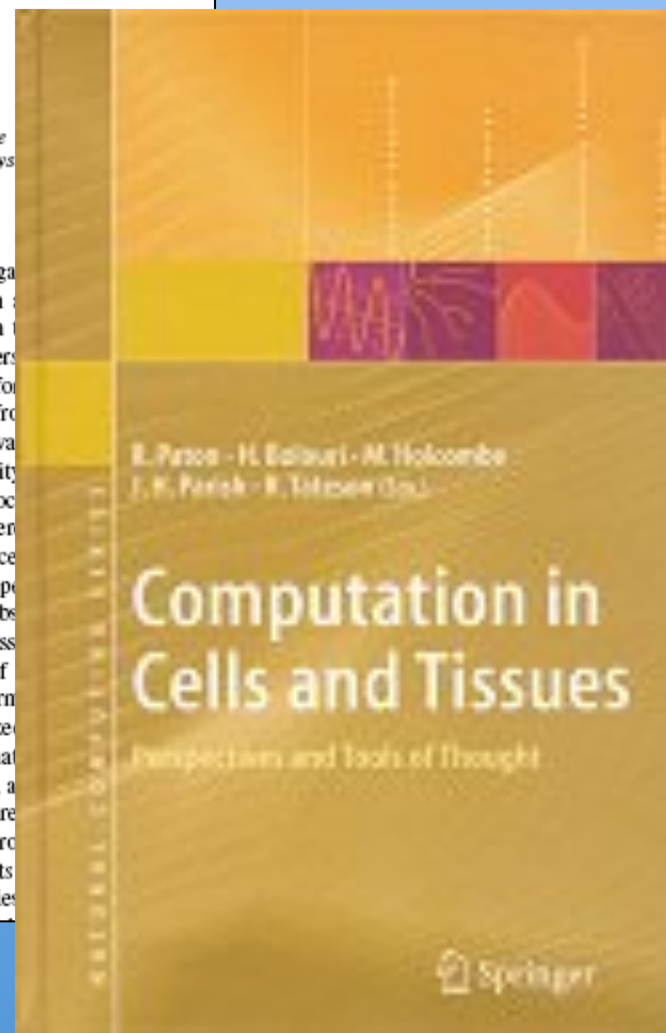
M. L. Simpson is with the Molecular Scale Engineering and Nanoscale Technologies Research Group, Oak Ridge National Laboratory, Oak Ridge, TN 37831-6006 USA, and also with the Department of Materials Science

Keywords—*Gene circuit simulation, gene
gene expression analysis, synthetic biology, sys*

I. INTRODUCTION

Gene circuits and networks have orga
information, and from this organization
complex processes of life emerge. From
school of thought has formed that considers
in a very fundamental sense, to be an infor
[1]. The biological substrate[1] differs fro
found in engineered systems in many wa
treme circuit density and interconnectivity
and operation deeply rooted within stoc
However, regardless of the substrate wher
information processing is the very essence
computer engineering, and it is from this pe
consider engineering in the biological subs

The genetic and biochemical process
the complex and versatile behavior of
highly functional, densely packed, inform
systems. Individual cells or self-organize
perform extremely complex functions tha
communication, navigation, cooperation, a
thesis. At the heart of this functionality are
regulatory circuits and networks that pro
in a manner similar to engineered circuits
with density, complexity, and capabilities



Evidence for complex, collective dynamics and emergent, distributed computation in plants

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Communicated by Marlan O. Scully, Texas A&M University, College Station, TX, November 24, 2003 (received for review January 24, 2003)

It has been suggested that some biological processes are equivalent to computation, but quantitative evidence for that view is weak. Plants must solve the problem of adjusting stomatal apertures to allow sufficient CO_2 uptake for photosynthesis while preventing excessive water loss. Under some conditions, stomatal apertures become synchronized into patches that exhibit richly complicated dynamics, similar to behaviors found in cellular automata that perform computational tasks. Using sequences of chlorophyll fluorescence images from leaves of *Xanthium strumarium* L. (cocklebur), we quantified spatial and temporal correlations in stomatal dynamics. Our values are statistically indistinguishable from those of the same correlations found in the dynamics of automata that compute. These results are consistent with the proposition that a plant solves its optimal gas exchange problem through an emergent, distributed computation performed by its leaves.

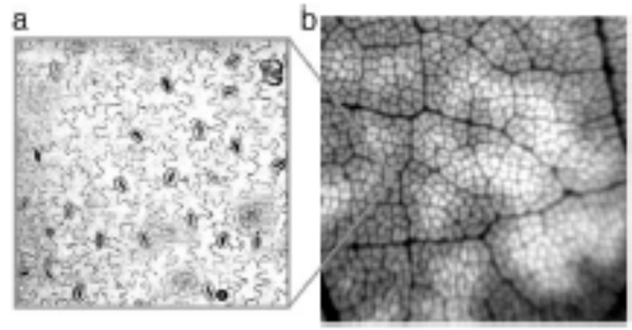
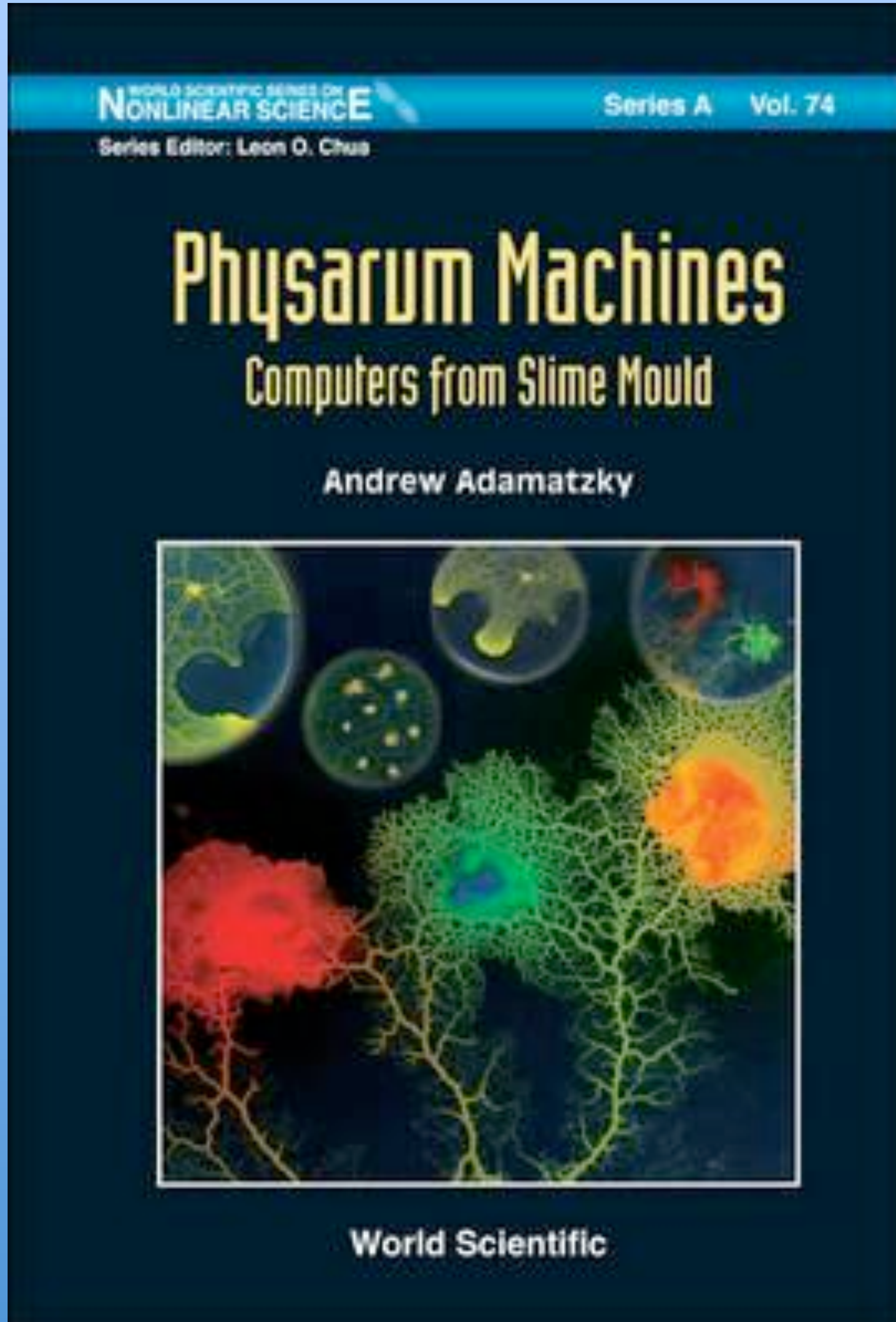


Fig. 1. (a) Confocal micrograph of a 0.56-μm^2 region of a leaf surface showing a field of (bean-shaped) stomata. (b) Near-infrared image of a 6.25-cm^2 region of a leaf surface showing patchy chlorophyll fluorescence. The image is brighter where the leaf's stomata are more closed.

Although biological and computational systems appear to share many analogous structures and processes (1), rigorous, nontrivial connections between life and computation remain elusive. One difficulty is that the biological systems that have been most actively investigated for evidence of computation (macroscopic organisms with neuronal networks, on the one hand, and proteins and nucleic acids participating in tangled webs of chemical reactions, on the other) are built from elements that interact irreducibly with vast numbers of each other. Such highly interconnected systems are notoriously hard to adequately describe mathematically. Support for the existence of sophisticated computation in biology (if it exists) is probably more likely to be found in systems in which the *relevant* elements interact

A central paradigm of plant biology is that, in the face of spatially heterogeneous and temporally varying environmental conditions, a plant continually adjusts stomatal aperture so that, over time, it maximizes CO_2 uptake for a fixed amount of water loss (3). The problem is made more difficult because it has to be solved at the level of the entire organism *but* without the aid of neuronal tissue capable of transmitting signals and coordinating activities over widely separated portions of the plant. Despite decades of intense study, how this is accomplished is not yet completely understood. The aperture of one stoma certainly adjusts to local microenvironmental conditions, and, for many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Comparing information processing in computer science and in biology

What plays the role of information in the system?

Computer Science: Digital, static, "passive" 0s and 1s on tape

Biology: "Active" analog patterns distributed in space and time over the system's components.

Information is represented via patterns of individuals and their products.

Information is gathered via local statistical sampling from these patterns.

Comparing information processing in computer science and in biology

How is information processed?

Computer Science: **Via deterministic , serial , error-free, centralized rules for reading, moving, and writing**

Biology: **Via decentralized, local , fine-grained stochastic actions.**

There is an interplay of positive and negative feedback.

- **Positive: recruitment, reinforcement**
- **Negative: competition, density limitations**

Randomness is ubiquitous, and is used by the system to its advantage.

Language of dynamical systems may be more useful than language of computation.

Comparing information processing in computer science and in biology

4. How does this information acquire function, purpose, or meaning?

   Computer Science: Human interpretation / purpose

   Biology: Natural selection for adaptive function.

Biologically Inspired "Self-Organized" Computing

Desire for "life-like" computing systems with emergent behavior from simple rules!

Biologically Inspired "Self-Organized" Computing

Biology		Computer Science
Ant foraging	→	Ant-Colony Optimization
Firefly synchronization	→	Distributed synchronization
Darwinian evolution	→	Genetic Algorithms
Brains	→	Neural Networks
Immune systems	→	Immune-System-Inspired Security
Slime moulds	→	Slime Mould-Inspired Search Algorithms