Introduction to Neuroscience
Neuromorphic Engineering

'Organizing principles' in neural and neuromorphic electronic systems

Part 1: Motivation, history, community
Part 2: Organizing principles
Part 2a: The physiologist's friend chip
Part 2b: The dynamic vision sensor

Tobi Delbruck
Inst. of Neuroinformatics
www.ini.unizh.ch/~tobi

Your neuroscience exam question will based on this lecture and the following reading

1. Mead, **Neuromorphic Electronic Systems**, Proc. IEEE, 1990
2. Delbruck & Liu, **A silicon visual system as a model animal**, Vision Research, 2004
3. Boahen, **Mimic the Nervous System with Neuromorphic Chips**, Scientific American, 2005

You can get these papers via the ZNZ Neuroscience Course web page.

Part 1: Motivation for neuromorphic engineering, history, community

Natural computation

Flies acrobatically
Recognizes patterns
Navigates
Forages
Communicates

10^{-15} J/op

Digital silicon 10^{-7} to 10^{-11} J/op

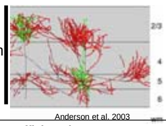
10^8 to 10^4 times as efficient as digital silicon

Computer vs. Brain

Pentium 4

Cortex

1mm



Anderson et al. 2003

At the system level, brains are about 1 million times more power efficient than computers. Why?

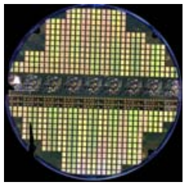
Cost of elementary operation (turning on transistor or synapse) is about the same. It's not some magic about physics.

Computer	Brain
Fast global clock	Self-timed
Bit-perfect deterministic logical state	Synapses are stochastic! Computation dances: digital→analog→digital
Memory distant to computation	Memory at computation
Fast high precision power hungry ADCs	Low resolution adaptive data-driven quantization
Devices frozen on fabrication	Constant adaptation and self-modification

Technology development has enabled this approach

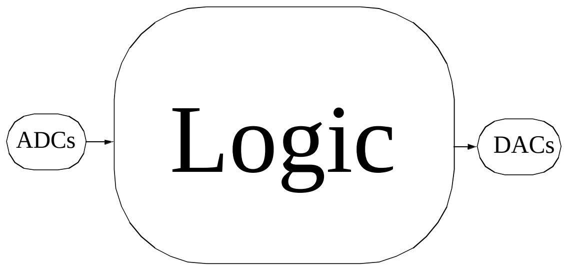
1947
1 transistor

1997
10^9 transistors

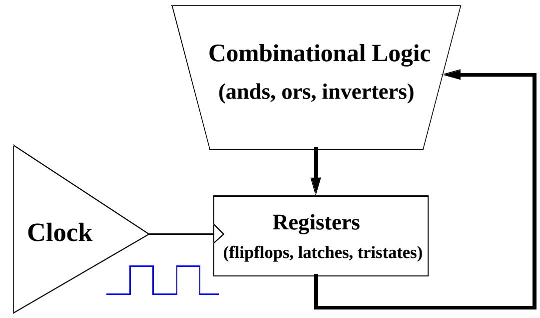


1. Moore's law: Number of transistors per chip doubles every 1.5 to 2 years
2. Cost/bit drops 29%/year
3. **True for last 45 years! Will continue at least another ~15y.**

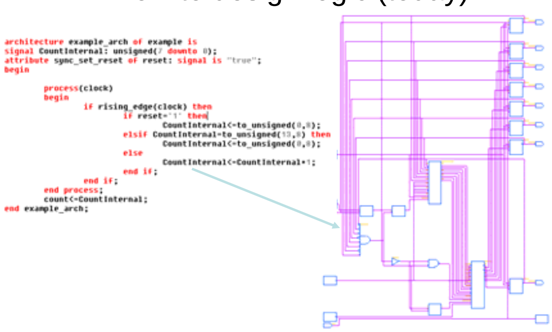
How industry thinks of analog design



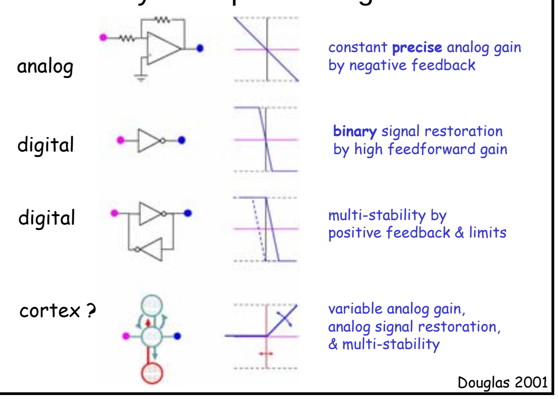
Synchronous logic



How to design logic (today)



styles of processing



Brief history of neuromorphic engineering

Physics of Computation Course

1982

1985


Carver Mead


Dick Feynman


John Hopfield

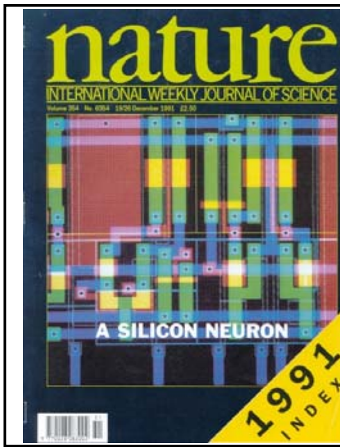
The World of Neuromorphic Engineering 2007

Shih-Chii Liu

Types of neuromorphic systems

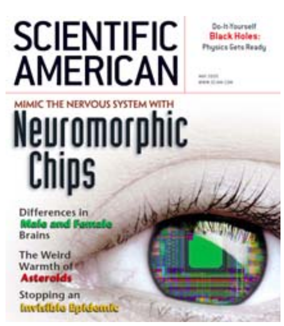
- **Silicon retinas**—electronic models of retinas
- **Silicon cochleas**—electronic models of cochleas
- **Smart sensors** (e.g. tracking chips, motion sensors, presence sensors, auditory classification and localization sensors)
- **Networks of spiking neurons** – with self-modifying adaptive synapses
- **Central pattern generators** – for locomotion or rhythmic behavior
- **Models of specific systems:** e.g. bat sonar echolocation, lamprey spinal cord for swimming, lobster stomatogastric ganglion, electric fish lateral line
- **Multi-chip systems** that use the *address-event representation* (spikes) for inter-chip communication

Accomplishments of neuromorphic engineering



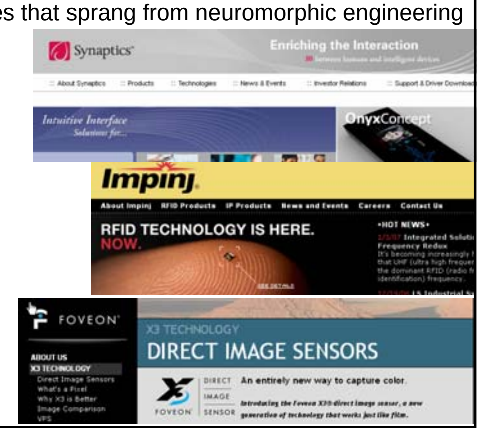
Mahowald, Douglas, 1991

Mahowald, Mead, 1991



Boahen, 2005

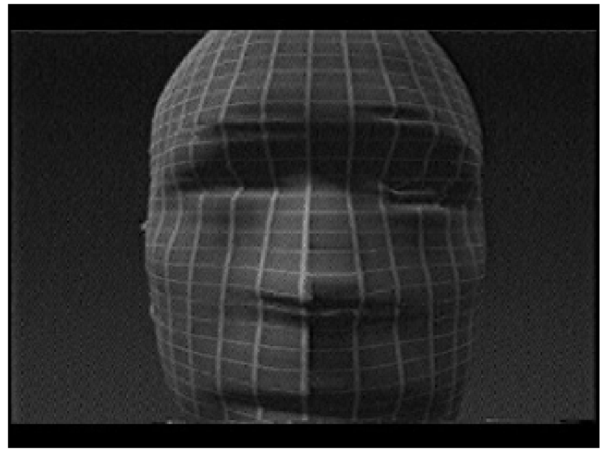
Companies that sprang from neuromorphic engineering



The Telluride Neuromorphic Engineering Workshop

- Focus is on
  - tutorials, hands-on workgroups
  - fostering the neuromorphic community
  - establishing long-lasting collaborations
- Running 12 years now, started by Rodney Douglas and Misha Mahowald.
- Funded by NSF & others, steadily at about $110k/yr.
- 60 people each year, about half invited and half applicants – **you can apply. Housing and part of travel is covered.**
- 3 weeks long each July, in the mountains in Colorado, USA.

Google "Telluride Neuromorphic" for more information



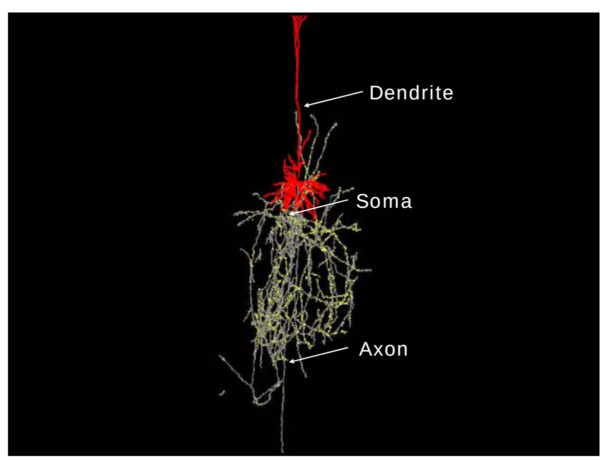
Part 2:
What are "organizing principles" as applied in neuromorphic engineering?

The fact that we can build devices that implement the same basic operations as those the nervous system uses leads to the inevitable conclusion that we should be able to build entire systems based on the organizing principles used by the nervous system.

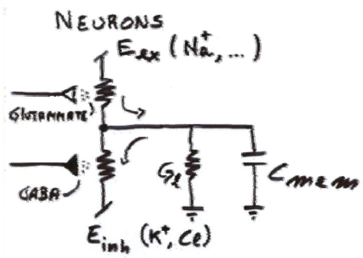
Mead, 1990

Complementary devices, amplification

(Example #1)



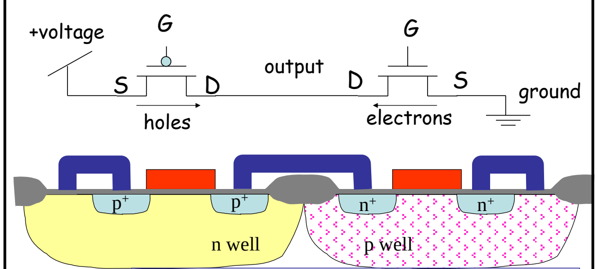
The membrane voltage is controlled by complementary channels



Almost no power is burned when both channels are off!

CMOS (complementary metal oxide semiconductor)

A CMOS inverting amplifier



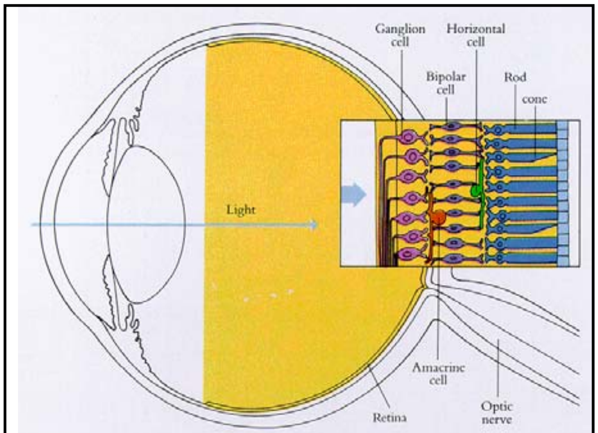
Organizing principle:
Use complementary devices to generate gain without burning excessive static power

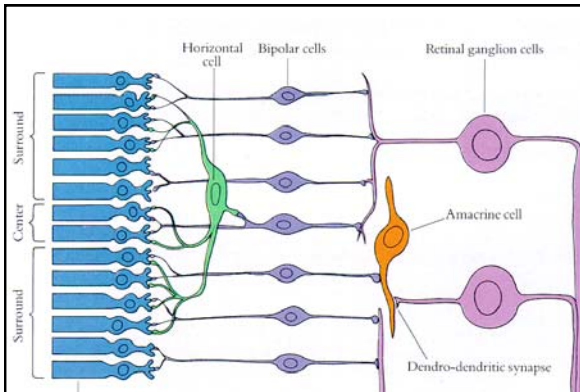
Mechanism of gain

Voltage sensitive channel conductance is exponential in membrane voltage	Transistor current is exponential function of gate voltage

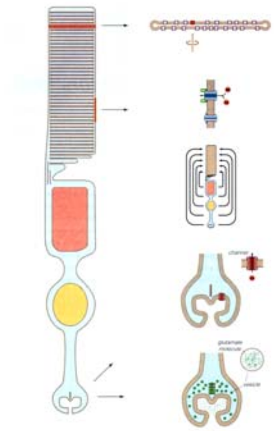
Organizing principle:
Use device physics (Boltzman distributions) to amplify

Part 2a:
Structure and function of the retina, as expressed in the "Physiologist's Friend Chip"



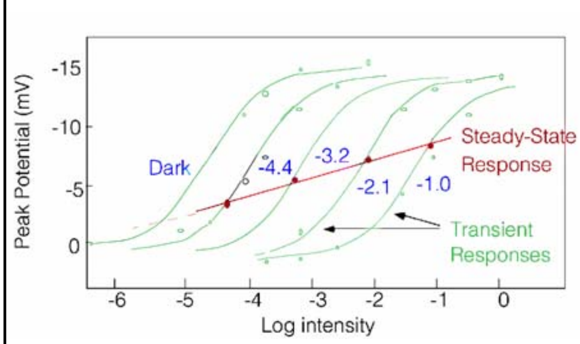


Rodieck 1998
The first steps in seeing



Rodieck 1998
The first steps in seeing

Biological photoreceptors adapt their operating point and gain



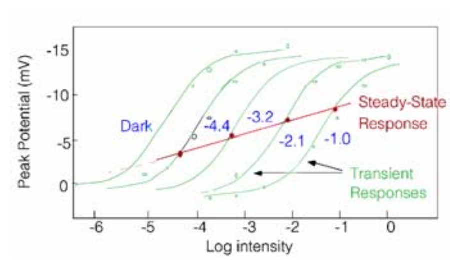
Norman & Perlman 1979

A logarithm is self-normalizing

$$d(\log X)=dX/X$$

Organizing principle: **Normalize** by value of signal

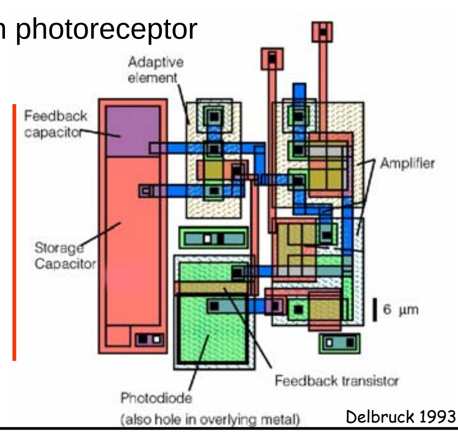
Biological photoreceptors adapt their operating point and gain



Organizing principle: **Use adaptation to amplify novelty**, not familiarity

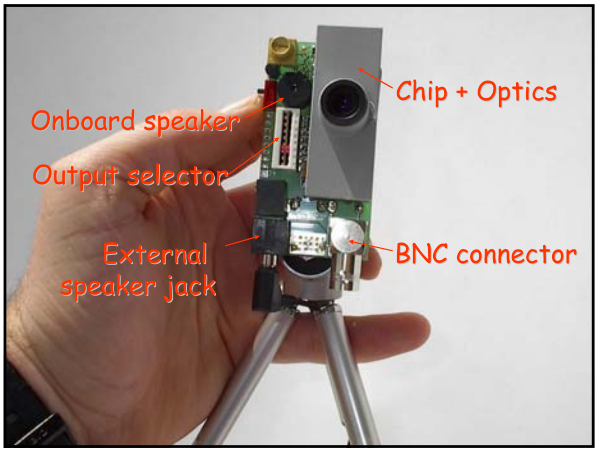
A silicon photoreceptor

<10μm
In today's technology

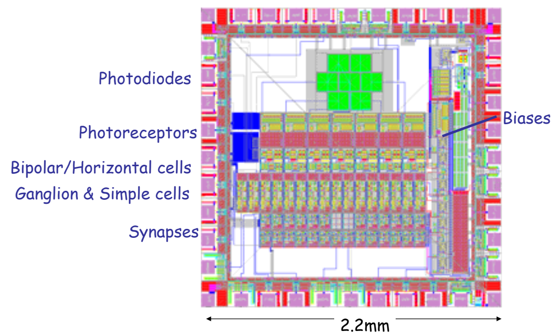


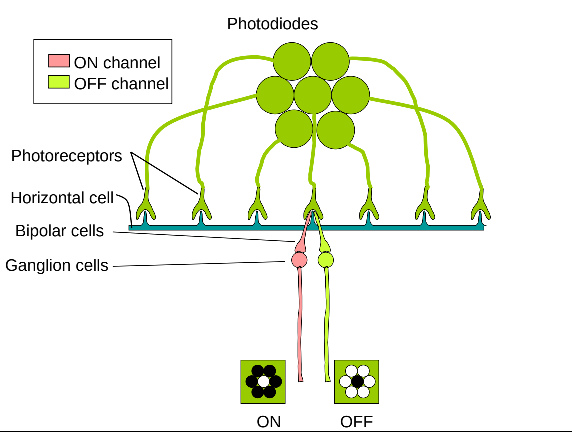
Delbruck 1993

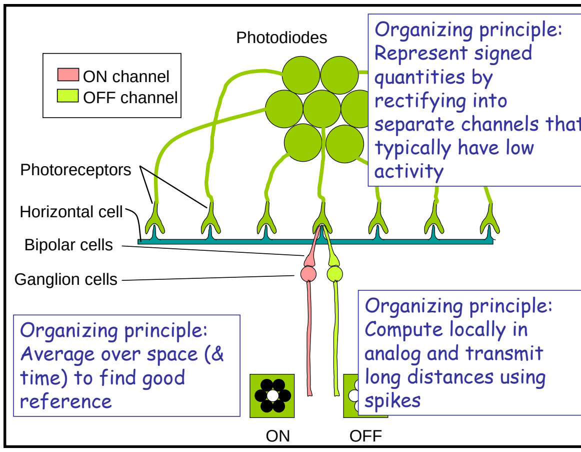
A Typical Visual Physiology Setup



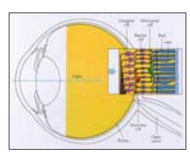
Physio Friend Chip Layout

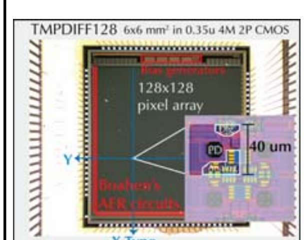






Part 2b:
The dynamic vision sensor
(asynchronous temporal contrast silicon retina)

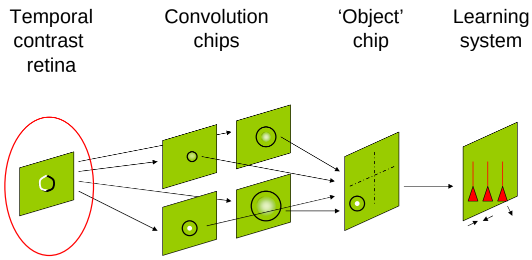




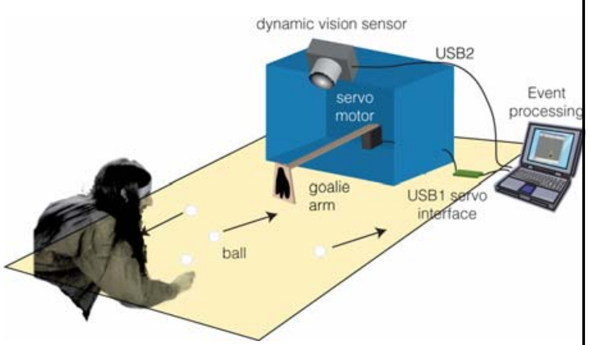
Dynamic vision sensor
1. This silicon retina ***asynchronously*** outputs ***pixel addresses (spikes)***.
2. The pixels respond to ***temporal contrast*** , like transient ganglion cells.

Lichtsteiner et al. ISSCC 2006

CAVIAR



Robot Goalie



Achieves 550 "FPS" and 3 ms reaction time at 4% processor load

Review: Organizing principles

1. **Use device physics for computation**
   1. Sum currents onto nodes
   2. Use capacitance to integrate over time
   3. Use Boltzman physics to amplify
2. **Use complementary devices to amplify without burning excessive static power**
3. **Average over space (& time)** to find correct context and reduce noise
4. **Normalize** by value of signal
5. **Represent signed quantities by rectifying** into separate ON and OFF channels
6. Use **adaptation** to **amplify novelty**, not familiarity
7. Compute **locally in analog**, **communicate remotely using events**

IF WE ARE TO AVOID THE AI TRAP
WE HAD BETTER EVOLVE OUR SYSTEMS
WITH REAL INPUT DATA
(BOTTOM UP)

THE AI TRAP:

1. ANNOUNCE INTENTION TO SOLVE AN OBVIOUSLY DIFFICULT PROBLEM
2. WORK LONG ENOUGH TO LEARN THAT IT IS MUCH MORE DIFFICULT THAN WAS INITIALLY SUPPOSED
3. FIND A TOY EXAMPLE THAT CONTAINS ONLY THE EASY PARTS OF THE PROBLEM
4. MAKE DEMO OF TOY EXAMPLE
5. DECLARE THE PROBLEM SOLVED WITHOUT REVEALING WHAT HAS BEEN LEARNED ABOUT THE HARD PARTS
6. GO TO STEP 1. OF A MORE DIFFICULT PROBLEM

Mead ca. 1990