Introductory Course in Neuroscience
Neuromorphic Engineering I

Neuromorphic Engineering

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http://www.ini.uzh.ch/~tobi/wiki/doku.php?id=introneuro

What is neuromorphic engineering?

It is embodying *organizing principles* of neural computation in electronics

Part 1: Motivation & history

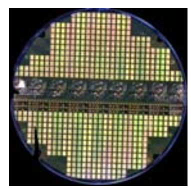
Part 2: Organizing principles

Part 3: Demonstrations of these organizing principles in the physiologist's friend chip and the dynamic vision sensor silicon retina

Artificial computation has been enabled by immense gains in silicon technology

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 of memory drops 29%/year
3. **True for last 45 years! Will continue at least another ~10y.**

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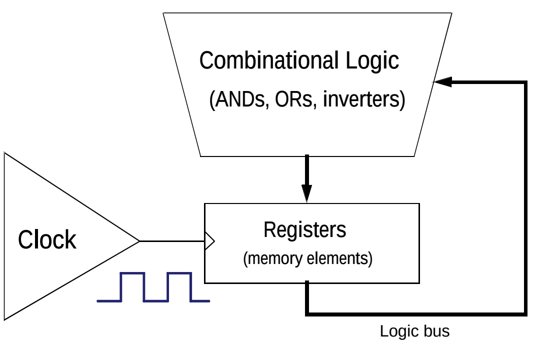
Synchronous logic is ubiquitous



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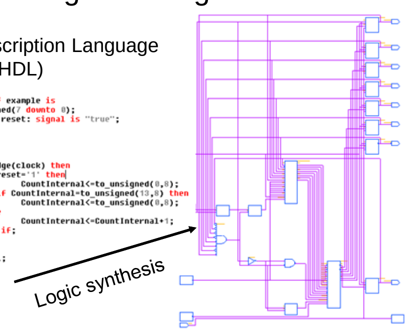
How logic is designed now

Hardware Description Language (HDL)

```
architecture example_arch of example is
signal CountInternal: unsigned(7 downto 0);
attribute sync_set_reset of reset: signal is "true";
begin

	process(clock)
	begin
		if rising_edge(clock) then
			if reset='1' then
				CountInternal<=to_unsigned(0,8);
			elsif CountInternal=to_unsigned(13,8) then
				CountInternal<=to_unsigned(0,8);
			else
				CountInternal<=CountInternal+1;
			end if;
		end if;
	end process;
	count<=CountInternal;
end example_arch;
```



By using HDLs, industry can routinely design complex chips with >100 million logic elements

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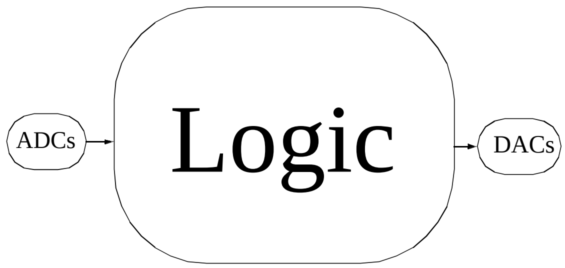
How industry uses analog processing



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Natural computation

Flies acrobatically
Recognizes patterns
Navigates
Forages
Communicates

At least a million times as efficient as digital silicon

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Computer vs. Brain

Computer	Brain
Fast global clock	Self-timed, data driven
Bit-perfect deterministic logical state	Synapses are stochastic! Computation dances digital→analog→digital
Memory distant to computation	Synaptic memory at computation
Fast, high resolution, constant sample rate analog-to-digital converters	Low resolution adaptive data-driven quantizers (spiking neurons)

Differences are currently possible because mobility of electrons in silicon is about 10^7 times that of ions in solution

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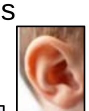
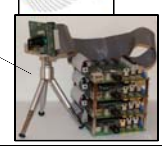
Types of neuromorphic systems

- **Neuromorphic Sensors** —electronic models of retinas and cochleas
- **Smart sensors** (e.g. tracking chips, motion sensors, presence sensors, auditory classification and localization sensors)
- **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 large-scale systems** that use the *address-event representation* (spikes) for inter-chip communication and are used for studying models of neuronal (cortical) computation and synaptic plasticity for learning

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Multi-chip large-scale systems

Four large projects have been in the news

SpiNNaker (Manchester)

SyNAPSE (DARPA/IBM)

Neurogrid (Stanford)

Brainscales/HBP (Heidelberg, Lausanne)

A Countdown to a Digital Simulation of Every Last Neuron in the Human Brain [Preview]

These projects all build (or use) specialized hardware for simulation of large numbers of strongly interconnected spiking neurons.

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Part 1: Motivation & history

Part 2: Organizing principles as adopted for neuromorphic electronic engineering

Part 3: Demonstrations of the Physiologist's Friend Chip and the dynamic vision sensor silicon retina

Examples of these organizing principles

1. **Using device physics for computation**
   1. Using charge to add and subtract by summing currents onto nodes
   2. Using capacitance to integrate over time
   3. Using controlled energy barriers to amplify
2. **Using complementary devices to avoid burning static power**
3. **Averaging over space & time** to control noise and find signal context
4. **Using context to normalize** signals
5. **Representing signed quantities by rectifying** into ON and OFF channels, again to avoid burning power to represent zero
6. Using **adaptation** to **amplify novelty** to overcome noise and imprecision
7. Computing **locally in analog** and **communicating remotely using events** to optimize use of power and reliably transmit information

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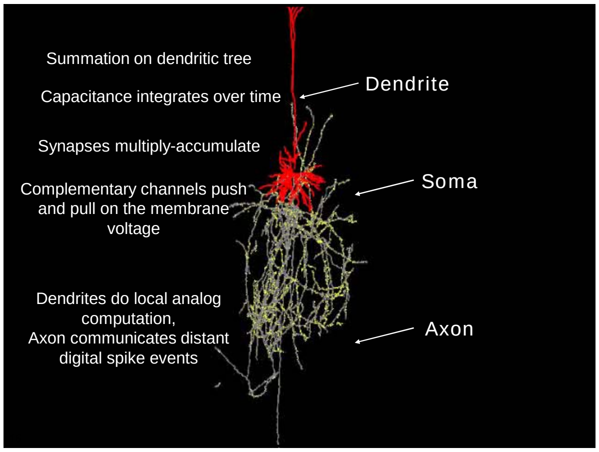
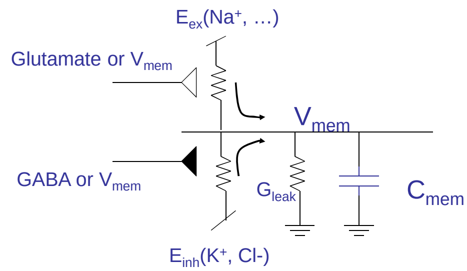
Let's see how principles #1 (device physics) and #2 (complementary devices) are used in neurons and electronics



The membrane voltage is controlled by **complementary** voltage- and neurotransmitter-gated channels



Little power is burned when both channels are off.

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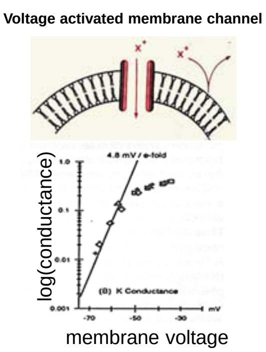
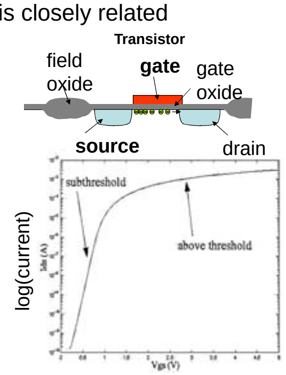
The physics of voltage activated membrane channels and transistors is closely related





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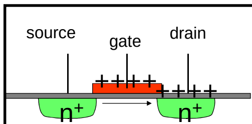
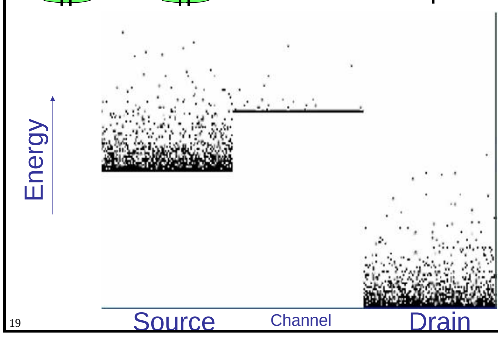
Metal-Oxide-Semiconductor (MOS) transistor operation





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Mechanism of *transconductance*

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

Organizing principle:
Use controlled energy barriers with Boltzmann energy distributions

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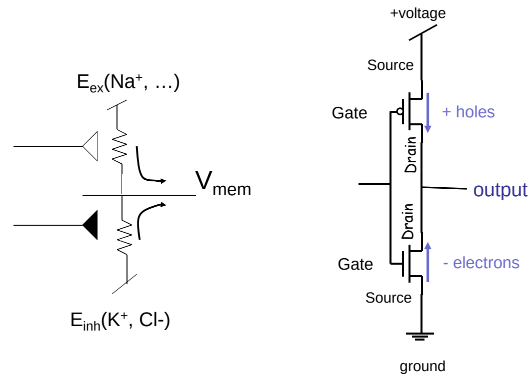
Complementary channels in biology and silicon



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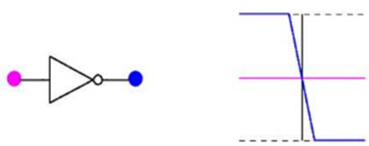
A digital inverter



Combinational logic (NAND, NOR etc) built the same way, by using parallel and series combinations of transistors

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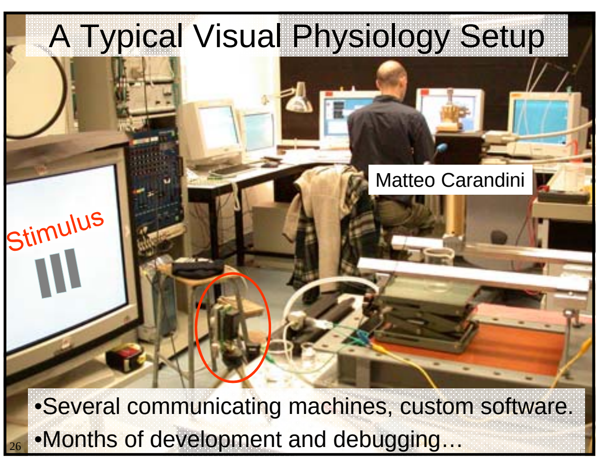
Part 1: Motivation & history

Part 2: Organizing principles

Part 3: Demonstrations of organizing principles using the *Physiologist's Friend Chip* and the *Dynamic Vision Sensor* silicon retina

A Typical Visual Physiology Setup



- Several communicating machines, custom software.
- Months of development and debugging…

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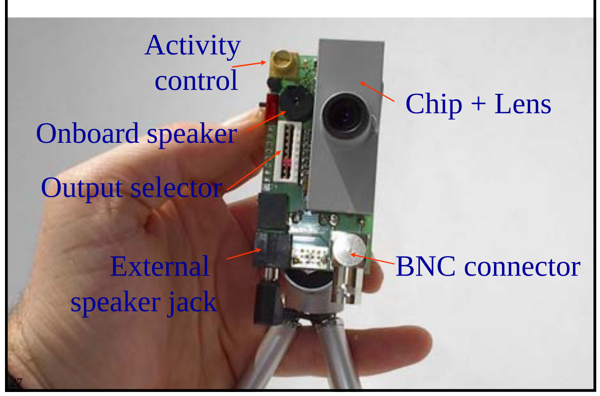
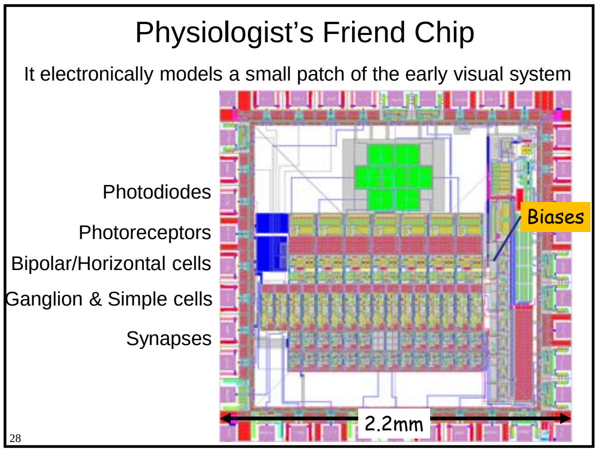
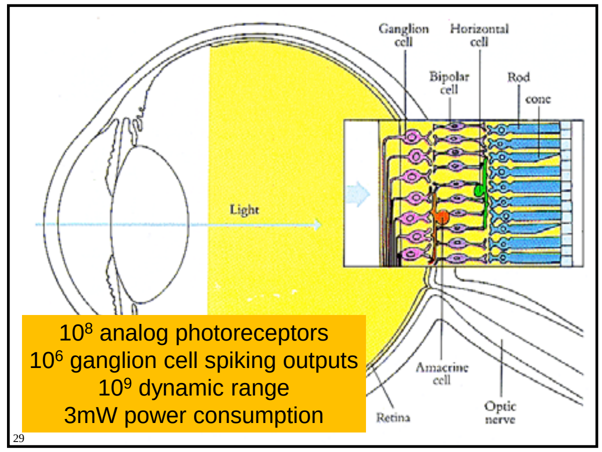
The Physiologist's Friend Chip




Physiologist's Friend Chip
It electronically models a small patch of the early visual system
Photodiodes
Photoreceptors
Bipolar/Horizontal cells
Ganglion & Simple cells
Synapses
Biases
2.2mm
28


Ganglion cell
Horizontal cell
Bipolar cell
Rod
cone
Light
Amacrine cell
Retina
Optic nerve
10^8 analog photoreceptors
10^6 ganglion cell spiking outputs
10^9 dynamic range
3mW power consumption
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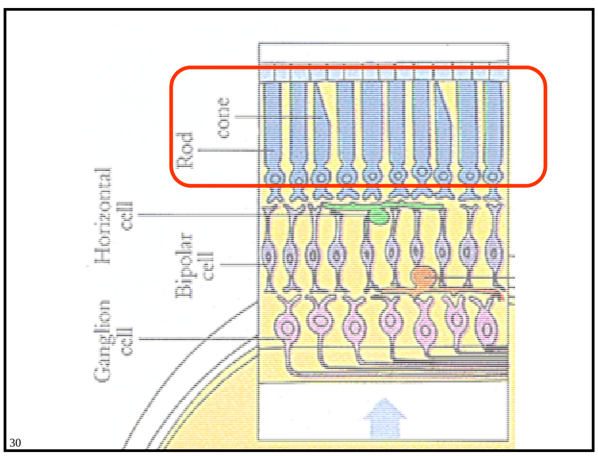
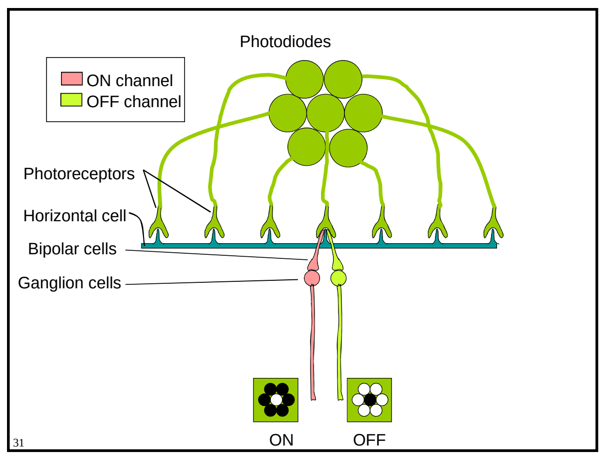

Rod
cone
Horizontal cell
Bipolar cell
Ganglion cell
30


Photodiodes
ON channel
OFF channel
Photoreceptors
Horizontal cell
Bipolar cells
Ganglion cells
ON
OFF
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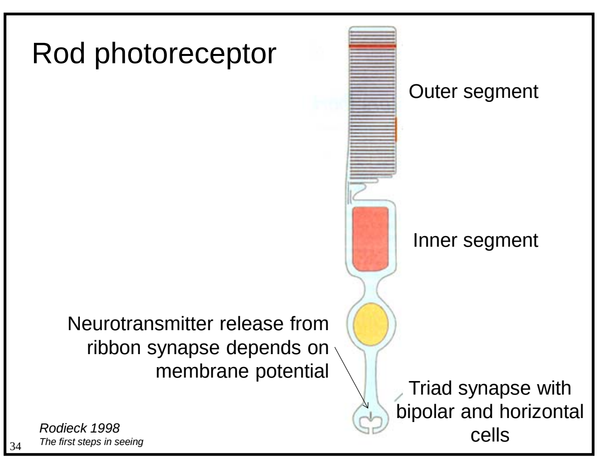
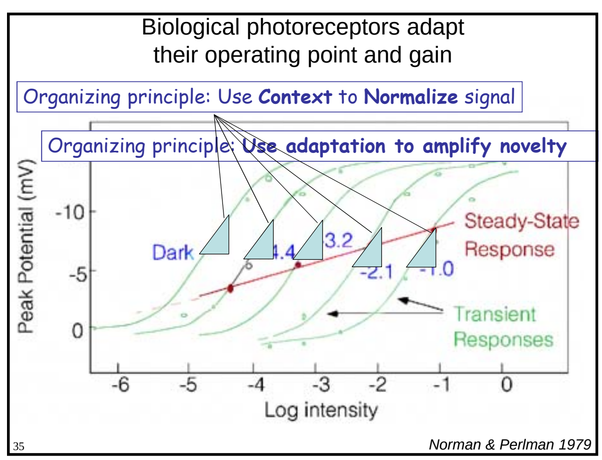

Rod photoreceptor
Outer segment
Inner segment
Neurotransmitter release from ribbon synapse depends on membrane potential
Triad synapse with bipolar and horizontal cells
Rodieck 1998
The first steps in seeing
34


Biological photoreceptors adapt their operating point and gain
Organizing principle: Use Context to Normalize signal
Organizing principle: Use adaptation to amplify novelty
Peak Potential (mV)
-10
-5
0
Dark
4.4
3.2
-2.1
-1.0
Steady-State Response
Transient Responses
-6
-5
-4
-3
-2
-1
0
Log intensity
Norman & Perlman 1979
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A logarithmic (or self-normalizing) representation of intensity is useful for representing object reflectance differences, rather than the illumination conditions.

- Two objects of different reflectance produce a ratio of luminance values.
- The difference of two log values represents this ratio, independent of the illumination.

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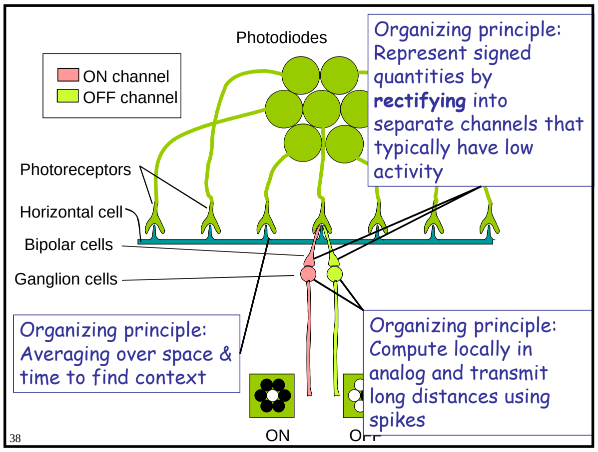

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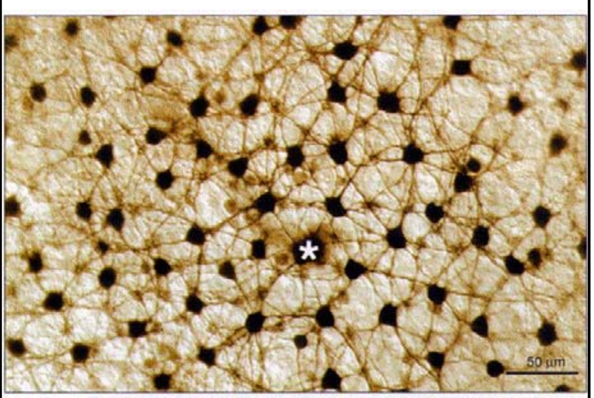

HI horizontal cells labeled following injection of one HI cell (*)

after Dacey, Lee, and Stafford, 1996

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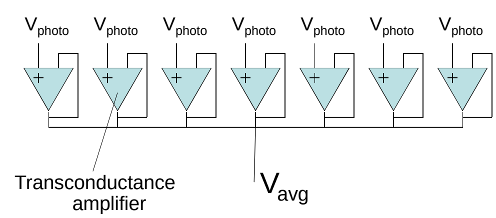
Horizontal cell

A "follower-aggregator" averages the photoreceptor outputs to compute the average of the inputs. This average is the *context* which the photoreceptor output is compared to.



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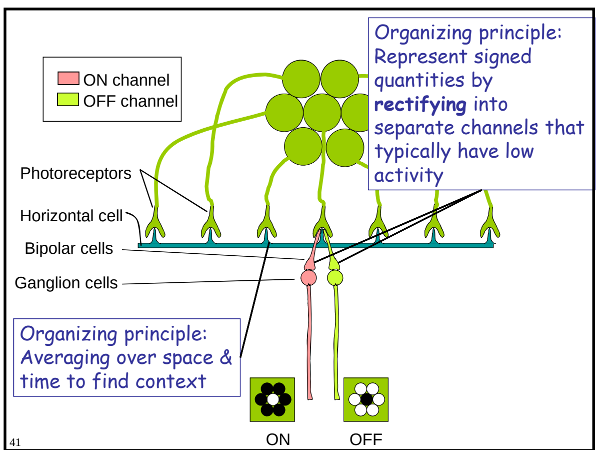

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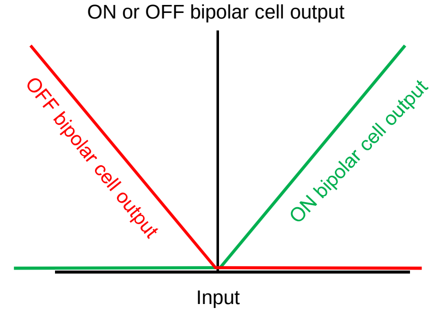
Rectification



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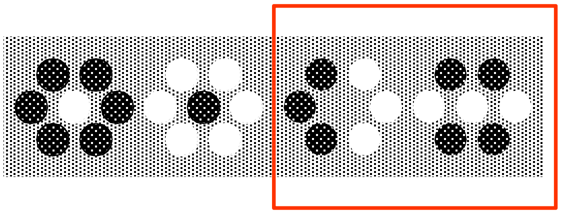
Receptive fields available on the Physiologist's Friend



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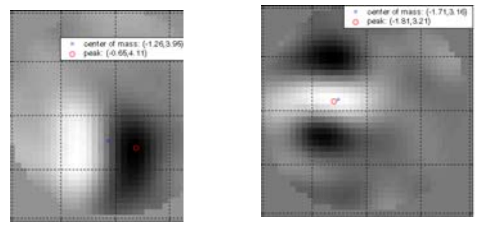
Spatial RFs of simple cells

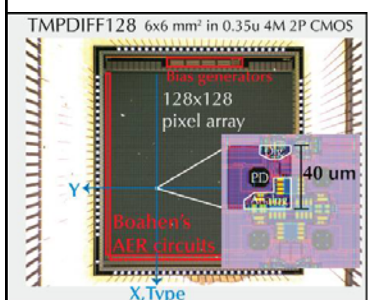
Measured by reverse spike correlation using random orientation stimuli



44 *Matteo Carrandini*

The dynamic vision sensor silicon retina

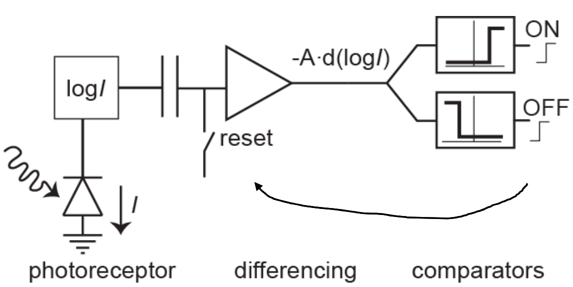
Dynamic Vision Sensor Silicon Retina (DVS)



1. The DVS ***asynchronously*** transmits ***address-events.***
2. The events represent ***temporal contrast*** , like transient ganglion cells.

47 Lichtsteiner et al. ISSCC 2006

Simplified DVS pixel architecture



Each event represents a change of log intensity

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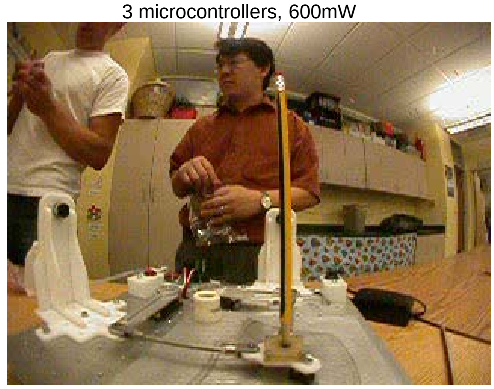
Embedded DVS Pencil Balancer

Jorg Conradt, Matt Cook

3 microcontrollers, 600mW



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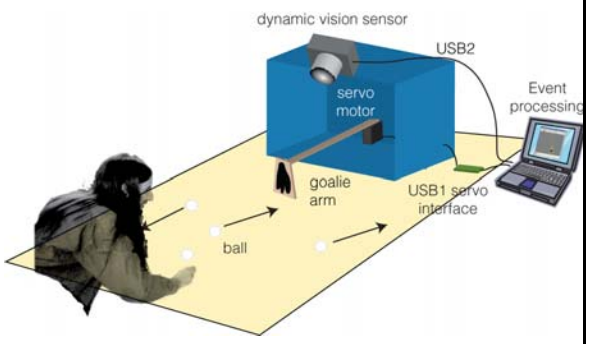
Robot Goalie



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

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Summary

1. Neuromorphic Engineering: Motivation, history, community
2. The use of “Organizing Principles”
3. Demonstrations of these organizing principles in the physiologist’s friend chip and the dynamic vision sensor silicon retina

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Resources

Background readingl:

- C. Mead (1990) **Neuromorphic Electronic Systems**, Proceedings of the IEEE, vol 78, No 10, pp 1629-1636 - *Carver Mead's summary paper on the rationale and state of the art in 1990 for neuromorphic electronics.*
- S.C. Liu, T. Delbruck (2010) **Neuromorphic Sensory Systems**, Curr. Opinions in Neurobiology - *Our recent review paper on neuromorphic sensors.*

Demonstrations

- T. Delbruck, S.C. Liu., **A silicon visual system as a model animal**, (2004). Vision Research, vol. 44, issue 17, pp. 2083-2089 - *About the electronic model of the early visual system demonstrated in the some class lectures (not in 2011).*
- **The Physiologist's Friend Chip** - *The electronic model of the early visual system demonstrated in the lecture.*
- **Jorg Conradt's Pencil Balancing Robot**
- **Dynamic Vision Sensor** - *Describes the dynamic vision sensor silicon retina demonstrated in the lecture.*

Yet more historical material and background:

- **Original silicon retina paper** from Scientific American, Misha Mahowald and Carver Mead, 1991
- K. Boahen (2005) **Neuromorphic Microchips**, Scientific American, May 2005, pp. 56-63 - *Kwabena Boahen's paper on the state of the art (in his lab) in 2005 in neuromorphic multi-chip systems.*

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