Neural Engineering

0.1. Contents

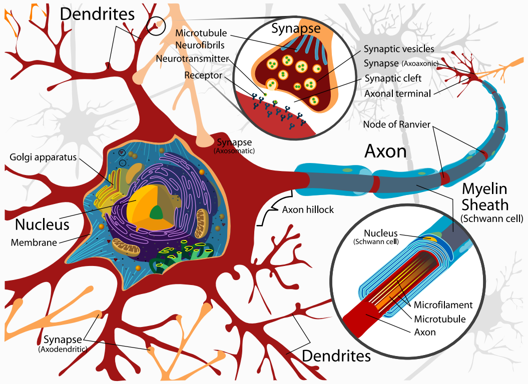
Learning Systems, Neural Vision
Neural Motor Control, Computional Neuroscience, Hardware Systems for Simulation
Neuro-Electronics, Neural Prostheses
3 weeks class project!

1. Neural Networks

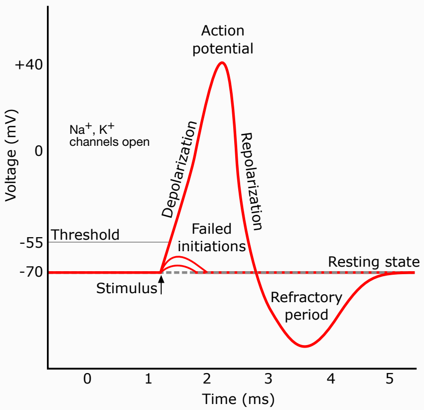
1.1. The Brain

$1.3\,\mathrm{kg}$ (2% of body weight) with 10×10^{11} neurons
10×10^{14} stochastic snapses, operating frequency $\le 100\,\mathrm{Hz}$
neuron growth $250.000\ \frac{1}{\mathrm{min}}$ (ealry pregnancy) and a loss of $1\ \frac{1}{\mathrm{s}}$
$20\,\mathrm{W}$ power consumption (25 % of body)

1.2. The Neuron

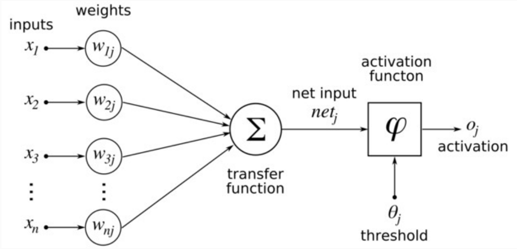


1.2.1 Action Potential



1.3. Artificial Neural Networks

Unserstand Biology ↔ technical abstraction



Several Inputs → Body → Single Output

$$out = f\left(\sum_i w_i \cdot in_i\right)$$

Problem in networks: Error in intermediate layers is unknown. we cannot adjust weights.
Solution: Error Backpropagation learning
Concept: Backpropagate Error from output layer to previous layers based on neural activity. ⇒ very slow learning

Goal: Toroidal Network (Hexagonal Shape, no ends, multiple paths possible)

2. Neural Vision

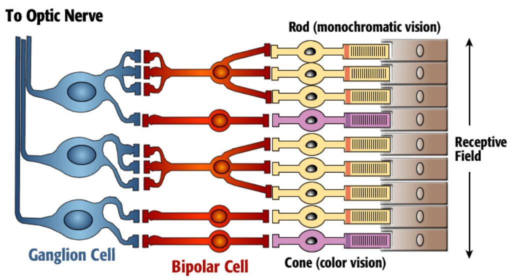
2.1. The Eye

Main spot: Fovea Blind Spot: Nerve bunch
120M rods(light), 6M cones(color)

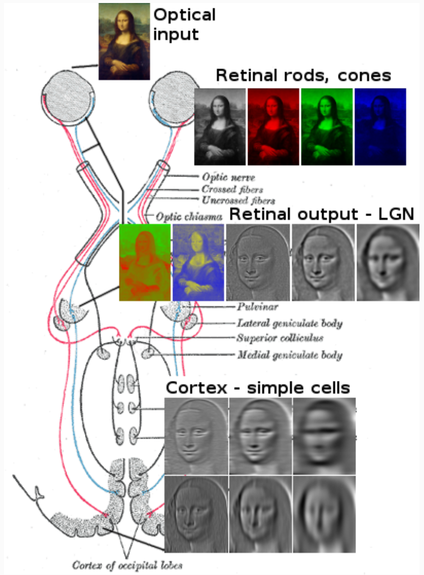
Working Principle rods: Light → Protein Rhodopsin → activates transducin G-protein → hyperpolarization → change rate of photoreceptors
Bipolar cells work with graded potentials, not with spikes!

2.1.1 Ganglion-cells

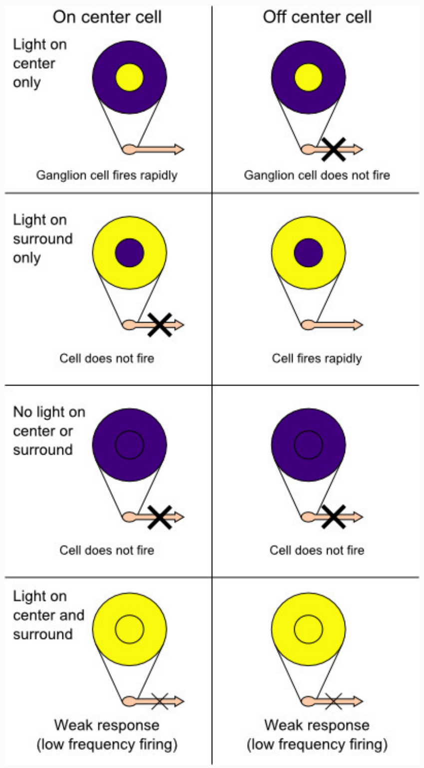
M-cell: respond to stimulations with a burst of spikes
P-cell: sustained discharge as long as the stimulus is present



2.2. Visual Pathway



2.3. Receptive Field



2.4. Neural Vision

Binding Problem: Which features (color, orientation, edges) belong to one object an not the other?
Translational, rotational, and scaling invariance
Feature detectors operate in parallel, mainly feed forward, but many recurrent connections.
High areas become smaller but receptive fields become larger and more complex.

2.5. Cortex Principles - Edge Detection

Sobel Operator Input $I \in \mathbb{R}^{m \times n}$

$$\boldsymbol{G}_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \cdot \boldsymbol{I} \qquad \boldsymbol{G}_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \cdot \boldsymbol{I}$$

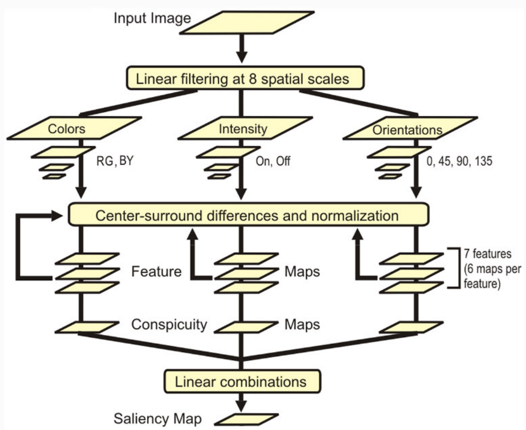
$$\boldsymbol{G} = \sqrt{\boldsymbol{G}_x^2 \cdot \boldsymbol{G}_y^2}$$

Gabor Filtering (Cosine within gaussian function)

$$g(x,y) = \exp\left(\frac{\tilde{x}^2 + \gamma^2 \tilde{y}^2}{2\sigma^2}\right) \cdot \cos\left(2\pi \frac{\tilde{x}}{\lambda} + \varphi\right)$$

2.6. Saliency Maps

Visual Attention for Rapid Scene Analysis



Center-Surround differences and normalization:
12 color maps: $RG(c,s) = |R(c) - G(c)\theta(G(s) - R(s))|$
6 intensity maps: $I = \frac{(r+g+b)}{3}$
24 orientation maps: $G = \{0°, 45°, 90°, 135°\}$
Normalization to $[0 \dots M]$: find global max M, compute average $\overline{m}$ of all other local maxima, multiply input map by $(M - \overline{m})^2$
Across-scale combination and normalization:
$\overline{I}, \overline{C}, \overline{O}$
Set your Focus of Attention (FoA) Winner takes all network
Then inhibit the spot to get another spot in the next round!

2.7. Optic flow

2.8. Motion Perception

Insect Motion Perception: Hassenstein-Reichhardt Detector Human Motion Perception: Optic Flow
Aquire image pairs at time t and $t-1$

3. Neural Vision: Neural Motor Control

Event Based Dynamic Vision System (eDVS) Only detect changes instead of receiving the same information all of the time.

3.1. DVS Sensors

Works like human retina: instead of sending full images at fixed frame rates, only the local pixel-level changes caused by movement in a scene are transmitted – at the time they occur.

reduction of data rate: only information of changing pixel

increased temporal resolution: lower latency, many asynchrone data, continous trajectory, no motion blur precision of time $1\ \mu s$

no frames:

can't detect motion: only on off events

Application: Pencil balancing

3.2. SLAM

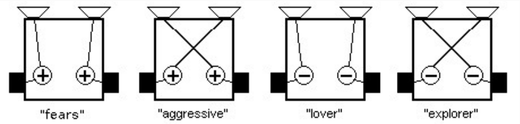
Self **L**ocalization **a**nd **M**apping: if you know your position, you can build a map easy if you have a map you can estimate your position easy. But if none of both is true it is difficult.

3.3. Motion Detector

Biology: Optic Flow, Richardt-Hassenstein eDVS: Calculate Δt between two pixel

3.4. Braitenberg vehicle

The vehicle represents the simplest form of behavior based artificial intelligence.



4. Computional Neuroscience

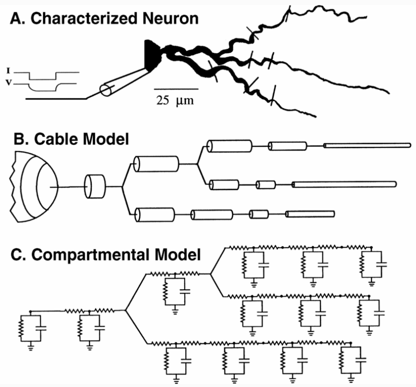
4.1. Projects

Blue Brain Project simulate one cortical column of a rat at ion-channel level

Human Brain Project 2013-2023

Spaun world's largest functional brain simulation

4.2. Neural Modeling Approaches



multi-compartment: cables modeled with resistors and capacitors

point neurons: only connections important, 0 compartment dimension, several spiking neuron models

mean field theory: spatiotemporal evolution of firing rate in populations of neurons

4.3. Spiking Neuronal Models

Poisson discrete probability

$\Pr(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}$

Information encoded in firing rate

Leaky Integrate and Fire (LIF) unrealistically simple

$\tau \dot{U} = -U_{\text{th}} + IR$

Firing Rate: $FR = \frac{1}{T_{\text{Ref}} + T_{\text{Spike}}}$

Hodgin-Huxley (HH) ODE 4th Order, too complex

K^+ current, Na^+ current, Leak current

Izhikevich ODE 1st Order, Good compromise

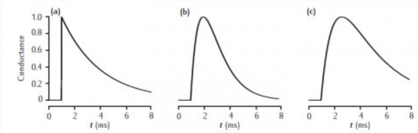
2 variables, 4 parameters

Adaptive Exponential LIF 2 variabels:

membrane potential V, adaption G_{adapt}

4.4. Synaptic Models

Conductance-based most often used



3 kinds of waves: (a) single exponential, (b) alpha function, (c) difference of exponential functions

Current-based Synapses as source of fixed amount of current

4.4.1 Synaptic plasticity modeling

Firing Rate Based: $\frac{\mathrm{d}W}{\mathrm{d}t} = f(x_i, y, W_i, \text{other})$

Spike Timings: Hebbian learngin: fire together, wire together

4.5. Neural Simulators

4.5.1 Clock driven (more popular)

All neurons are updated at every tick of a clock

Integration: Euler or Runge-Kutta

After update, check threshold condition

4.5.2 Event driven

Neurons are updated only when they receive or emit a spike. Exact spike time computation, but complex.

4.5.3 Simulators

NEURON 1994, biological neurons and neural circuits, single compartment soma and multi compartment axon

NEST 2004, large simulations of spiking neural networks, single/few compartments

BRIAN 2008, Easy to implement customized neuronal models, single compartment

PyNN 2008, Simulator-independent language, supports NEURON, NEST, BRIAN, Single IF neurons

Nengo 2003, Neural compiler, spiking neurons

5. Hardware Systems

5.1. Brain Data

brain-map.org

Alen brain Atlas

Brain Explorer

E.G.F.P.

5.2. What does it take to simulate my brain

10^{10} Neurons, 10^{14}

You need a Exascale Supercomputer (T,P,E) FLOPS

$0.5\,\text{GW}$ (100k Households)

Solution: Specialized Hardware!

5.3. Neural Hardware

spiNNaker Mesh of ARM cores, Manchester University

The Core: ARM968: 200MHz, 32kB instr., 64kB data, No FPU!

Can simulate about 1000 Neurons per Core in Real-Time!

One spiNNaker-Chip: 18 Cores + Router, 6 Forwards Outputs

Pros: standalone, extensible to 10^6 cores, supports PyNN

Cons: bottlenecks for mem in/out, high power consumption, beta-quality interfaces, not available commercialy

Neurocore 256×256 neurons, 2.3×10^6 transistors

60 float parameters, 18 binary,

Pro: Analog neurons and synapses, digital tree-router for spikes, 10^6 neurons, 10^9 synapses, only $3\,\text{W}$

Cons: not extensible, cant buy, no std. software

BrainScaleS purely analog neurons and synapses

HICANN chip: 512 neurons, but one neuron can receive spikes from 16k inputs

Pro: Wafer scale integration, faster than real-time (100kHz) **Cons:** inefficient: 0.18M neurons with 800W

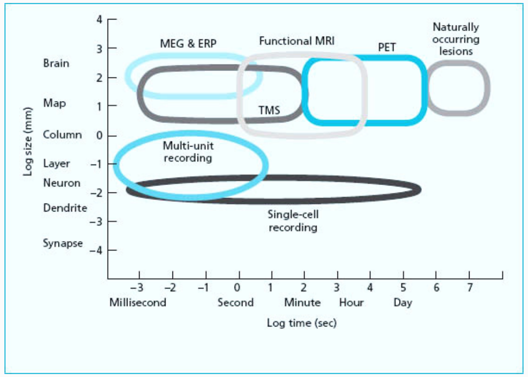
CrossNets nanodevice, define connections between neurons, need N^2 area to interconnect N neurons.

Neuristor No transistors, only capacitors and memristors

6. Neural Prostheses

Brain Computer Interface for Recording and Stimulation: Establish a bidirectional communication channel between the brain and an external device. Purposes: studies, diagnoses, assisting sensor/aktor in human body.

6.1. Resolution Comparison



6.2. Recording Techniques

Electroencephalography (EEG) Recording of electrical activity along the scalp. Higher frequencys have lower energy in the brain (need amplification)

Electrocorticography(ECoG): EEG directly placed on the brain.

Micro-electrode arrays: high density recording

Patch clamp: Recording of current from single ion channels.

Magnetoencephalography (MEG): Record magnetic field in range $10^{-15}\,\text{T}$.

Functional Magnetic Resonance Imaging (fMRI): Measures signal changes in the brain.

6.3. Stimulation Techniques

Micro-electrode arrays

Optogenetics: Ion channels are genetically modified to be photosensitive, Illumination is used to alter cellular behavior

Transcranial Magnetic Stimulation (TMS): Induces electric currents in the brain without physical contact, Treatment for depression

6.4. Electrophysiological experiments

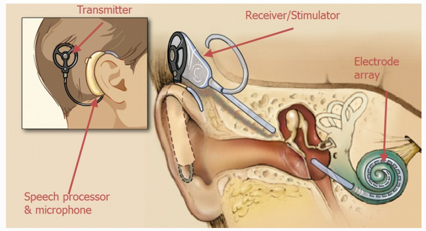
In vivo, In vitro, closed-loop Continious Stimulus to the brain can stop effects of parkinson deseases.

6.5. Neural Prostheses

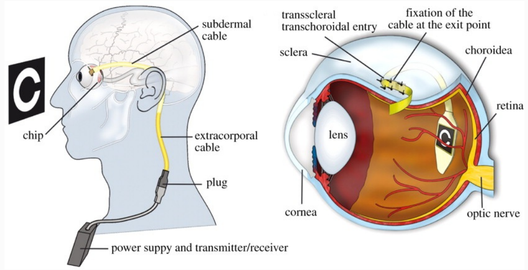
Purpose: restoring (or improving) lost sensory/motor functions

Challenges: Biocompatibility, Degeneration Nerve/Electrode, Encoding

Cochlear Implant: most popular, hearing aid



Retinal Implant: 2 Types: epiretinal, subretinal



7. Exam Questions

which digital architecures exists for ANN?