Introduction to Neural Networks & Neural Computation

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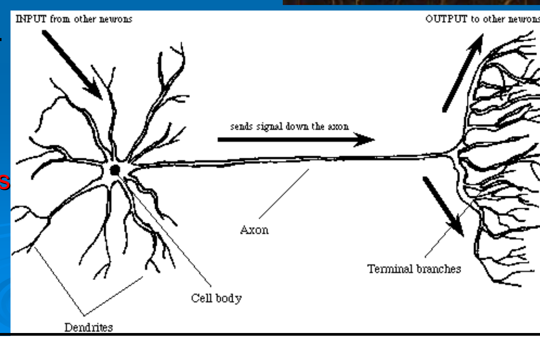
Presentation Overview

- Biological Neurons
- Artificial Neuron Abstractions
- Different types of Neural Nets
  - Perceptron
  - Multi-layer Feed-forward, Error Back-Propagation
  - Hopfield
- Implementation of Neural Nets
  - Chemical & biological systems
  - Computer Software
  - VLSI Hardware
- Alternative Model – Action Potential timing

The Biological Neuron

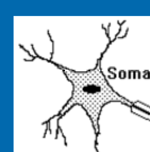
- Human Nervous system → 1.3x10^{10} neurons
  - 10^{10} are in brain
  - Each connected to ~10,000 other neurons
  - Power dissipation ~20W

- Neuron Structure:
  - Cell Body – Soma
  - Axon/Nerve Fibers
  - Dendrites
  - Presynaptic Terminals

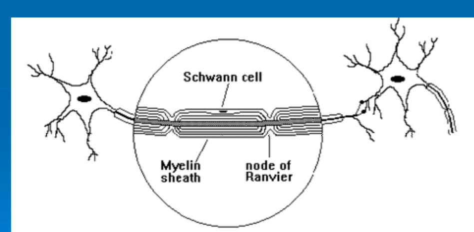


The Biological Neuron

- Cell Body – Soma
  - Includes Nucleus & Perikaryon
  - Metabolic Functions
  - Generates the transmission signal (*action potential)* – through *axon hillock* -, when received signal threshold reached

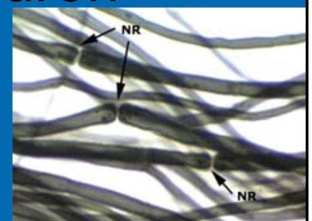


- Axon/Nerve Fibers
  - Conduction Component
  - 1 per neuron
  - 1mm to 1m
  - Extends from *axon hillock* to *terminal buttons*
  - Smooth surface
  - No ribosome



The Biological Neuron

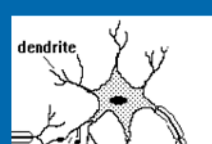
- Axon/Nerve Fibers –
  Myelin Sheath & Nodes of Ranvier



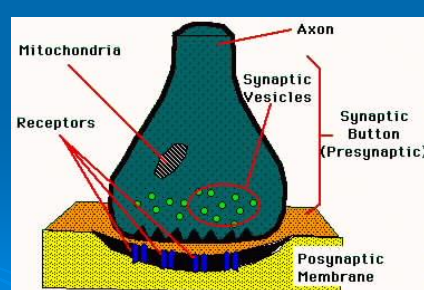
  - axons enclosed by myelin sheath
    → many layers of schwann cells
    → promote axon growth
  - Myelin sheath insulates axon from extracellular fluid: thicker myelin ➔ faster propagation
  - Myelin sheath gaps: Nodes of Ranvier
    → Depolarization occurs sequentially
    → trigger next node ➔ impulse propagates to next hop & restored at each node (buffering)

The Biological Neuron

- Dendrites
  - The receiver / input ports
  - Several Branched
  - Rough Surface (dendritic spines)
  - Have ribosomes
  - No myelin insulation

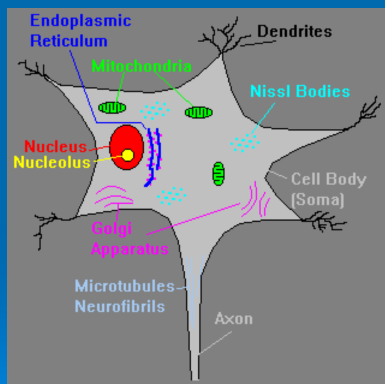


- Presynaptic Terminals
  - The branched ends of axons
  - Transmit the signal to other neurons' dendrites with *neurotransmitters*



The Biological Neuron

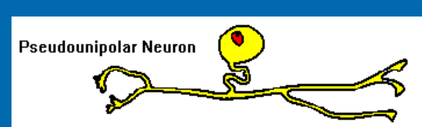
- Inside of a Neuron:

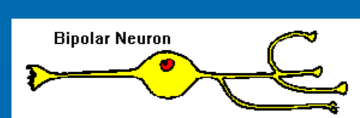


- Nucleus - genetic material (chromosomes)
- Nucleolus - Produces ribosomes : genetic information → proteins
- Nissl Bodies - groups of ribosomes → protein synthesis
- Endoplasmic reticulum (ER) - system of tubes → material transport in cytoplasm
- Golgi Apparatus - membrane-bound structure → packaging peptides and proteins (including neurotransmitters) into vesicles
- Microfilaments/Neurotubules - transport for materials within neuron & structural support.
- Mitochondria - Produce energy

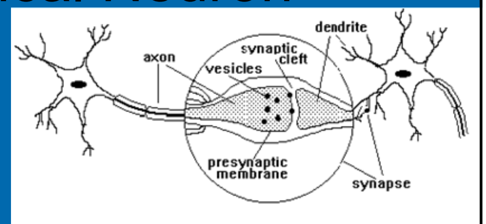
The Biological Neuron

- Neuron Types:
  - Unipolar Neuron
    - One process from soma → several branches
    - 1 axon, several dendrites
    - No dendrites from soma
  - PseudoUnipolar Neuron
    - 2 axons
  - Bipolar Neuron
    - 2 processes from soma
    - (PseudoUnipolar ← bipolar)
  - Multipolar Neuron
    - Single axon
    - Several dendrites from soma



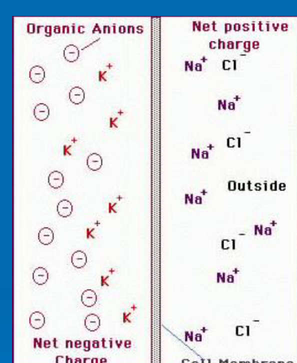


The Biological Neuron



- **Synapse:**
  - Junction of 2 neurons
  - Signal communication
  - Two ways of transmission:
    - Coupling of ion channels → Electrical Synapse
    - Release of chemical transmitters → Chemical Synapse
- Chemical Synapse:
  - Presynaptic neuron releases *neurotransmitters* through synaptic vesicles at terminal button to the synaptic cleft – the gap between two neurons.
  - Dendrite receives the signal via its receptors
  - [Excitatory & Inhibitory Synapses – Later]

The Biological Neuron

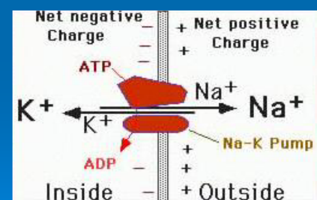


- **Membrane Potential:**
  - 5nm thick, semipermeable
  - Lipid bilayer controls ion diffusion
  - Potential difference ~70 mV
  - Charge pump:
    - Na^+ →
    - ← K^+

    → Outside Cell
    ← Into Cell
- Resting Potential:
  - When no signaling activity
  - Outside potential defined 0
    - → Vr = ~ -70mV

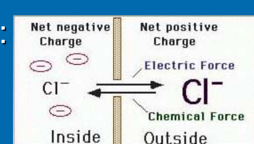
The Biological Neuron

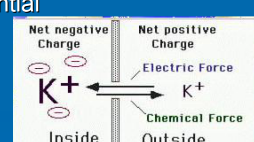
- Membrane Potential – Charge Distribution:
  - Inside: More K^+ & Organic Anions (acids & proteins)
  - Outside: More Na^+ & Cl^-
  - 4 Mechanisms that maintain charge distribution = membrane potential:
    - 1) Ion Channels:
      - Gated | Nongated
      - Selective to specific ions
      - Ion distribution ← channel distribution
    - 2) Chemical Concentration Gradient
      - Move toward low gradient
    - 3) Electrostatic Force
      - Move along/against E-Field
    - 4) Na-K Pumps
      - Move Na & K against their net electrochemical gradients
      - Requires Energy → ATP Hydrolysis (ATP → ADP)

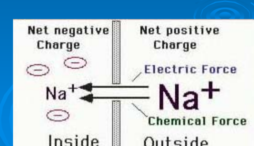


The Biological Neuron

- Membrane Potential – Charge Distribution:
  - Cl^- :
    - Concentration gradient ←
    - Electrostatic Force →
    - Final concentration depends on membrane potential
  - K^+ :
    - Concentration gradient →
    - Electrostatic Force ←
    - Na-K pump ←
  - Na^+ :
    - Concentration gradient ←
    - Electrostatic Force ←
    - Na-K pump →





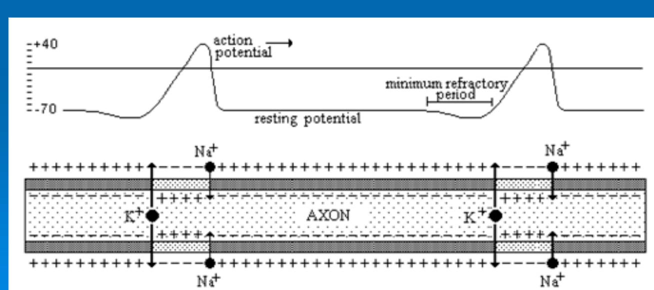


The Biological Neuron

- Excitatory & Inhibitory Synapses:
  - Neurotransmitters → Receptor sites at postsynaptic membrane
  - Neurotransmitter types
    - Increase Na-K pump efficiency
      - ➔ Hyperpolarization
    - Decrease Na-K pump efficiency
      - ➔ Depolarization
  - Excitatory Synapse:
    - Encourage depolarization
      ← Activation decreases Na-K pump efficiency
  - Inhibitory Synapse:
    - Encourage hyperpolarization
      ← Activation increases Na-K pump efficiency

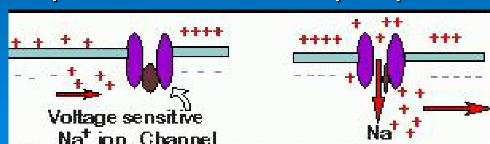
The Biological Neuron

- <u>Action Potential:</u>
  - Short reversal in membrane potential
    - ➔Current flow: Action Potential → Rest Potential
    - ➔Propagation of the depolarization along axon



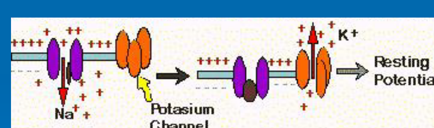
The Biological Neuron

- Action Potential:
  - Sufficient Excitatory Synapses Activation – Depolarization of Soma
    → trigger action potential:
    - Some Voltage gated Na Channels open
      ➔ Membrane Na Permeability Increases
      ➔ ← Na^+ ➔ Depolarization increases
      Positive Feedback
    - Depolarization builds up exponentially…



The Biological Neuron

- Action Potential:
  - Cl^- : Electrostatic Force '→' decreases
    ➔ more Cl^- ←
  - K^+ : Electrostatic Force '←' decreases
    ➔ more K^+ →
  - These cannot cease depolarization
- Repolarization:
  - Termination of action potential
  - 2 Processes:
    - Inactivation of Na Channels
      - Na channels have 2 types of gating mechanisms:
        - Activation during depolarization → open Na Channels
        - Inactivation after depolarization → close Na Channels
    - Delayed Activation of Voltage gated K Channels
      - ➔ more K^+ '←' ➔ more Na^+ '→'



The Biological Neuron

- Action Potential – Complete Story:
  - Neurotransmitters → Dendrites Receptors
    ➔ Initiate synaptic potential
  - Potential spreads toward initial axon segments
    - Passive excitation – no voltage gated ion channels involved
  - Action potential initiation at axon hillock
    ← highest voltage gated ion channel concentration
    - Happens if arriving potential > voltage gated channel threshold
  - Wave of depolarization/repolarization propagates along axon
  - Turns on transmission mechanisms at axon terminal
    - Electrical or Chemical Synapse

The Biological Neuron

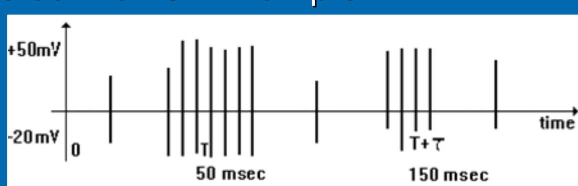
- Refractory Period:
  - Once an action potential passes a region, the region cannot be reexcited for a period ~1ms
    - Depolarized parts of neuron recover back to resting potential ← Na-K pumps
    - Max pulse rate ~1Khz
  - ➔ Electrical pulse propagates in a single direction
    - Inverse hysteresis?
    - Mexican wave
  - Electrical signals propagate as *pulse trains*

The Biological Neuron

- Pulse Trains:
  - Non-digital signal transmission nature
  - Intensity of signal → frequency of pulses
    - Pulse Frequency Modulation
  - Almost constant pulse amplitude
  - Neuron can send pulses arbitrarily even when not excited!
    - Much Less Frequency - Noise

The Biological Neuron

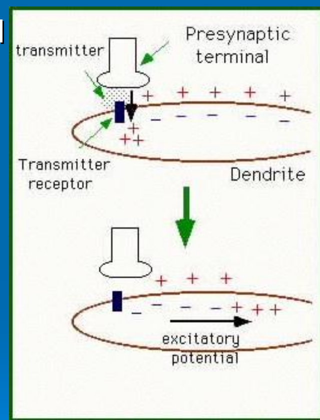
- Pulse Trains - Example:



  - t=0 → Neuron Excited
  - t=T [~50ms]→ Neuron fires a train of pulses
  - t=T+τ → Neuron fires a second set of pulses Due to first excitation
    - Smaller # of pulses
  - Neuron sends random less frequent pulses

Biological Neuron: Processing of Signals

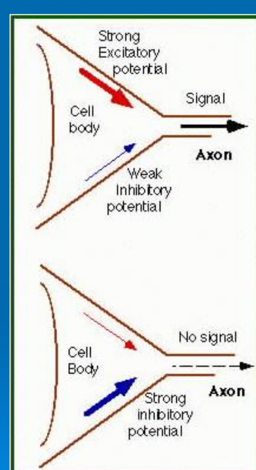
- A cell at rest maintains an electrical potential difference known as the resting potential with respect to the outside.
- An incoming signal perturbs the potential inside the cell. Excitatory signals depolarizes the cell by allowing positive charge to rush in, inhibitory signals cause hyper-polarization by the in-rush of negative charge.



http://www.ifisiol.unam.mx/Brain/neuron2.htm

Biological Neuron: Processing of Signals

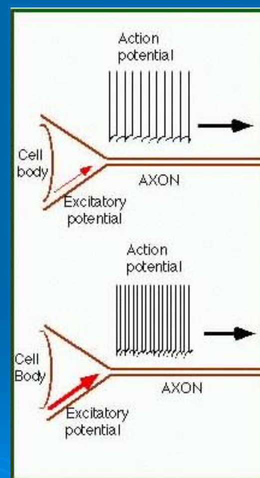
- Voltage sensitive sodium channels trigger possibly multiple "action potentials" or voltage spikes with amplitude of about 110mV depending on the input.



http://www.ifisiol.unam.mx/Brain/neuron2.htm

Biological Neuron: Conduction in Axon

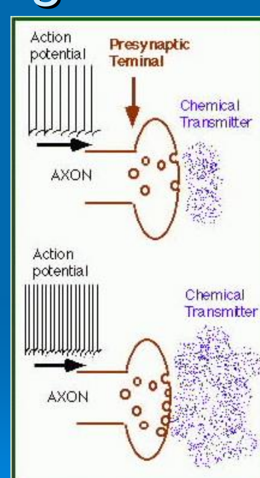
- Axon transmits the action potential, regenerating the signal to prevent signal degradation.
- Conduction speed ranges from 1m/s to 100m/s. Axons with myelin sheaths around them conduct signals faster.
- Axons can be as long as 1 meter.



http://www.ifisiol.unam.mx/Brain/neuron2.htm

Biological Neuron: Output of Signal

- At the end of the axon, chemicals known as neurotransmitters are released when excited by action potentials.
- Amount released is a function of the frequency of the action potentials. Type of neurotransmitter released varies by type of neuron.



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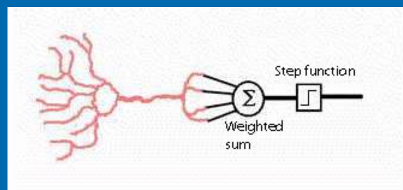
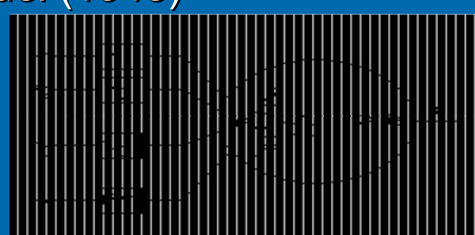
Artificial Neuron Abstraction



- Neuron has multiple inputs
- Inputs are weighted
- Neuron “fires” when a function of the inputs exceed a certain threshold
- Neuron has multiple copies of same output going to multiple other neurons

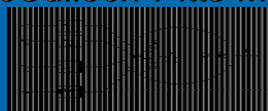
Artificial Neuron Abstraction

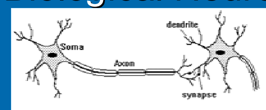
- McCulloch-Pitts Model (1943)
  - I/ps:[u1…uN]
  - Weights:[w1…wN]
  - θ:Threshold/bias
    - θ < 0 → Threshold
    - θ > 0 → Bias
  - Activation: 
  - O/p: x
  - O/p function/Activation function: x=f(a)



Artificial Neuron Abstraction

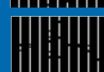
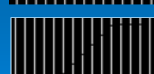
- McCulloch-Pitts Model vs. Biological Neuron





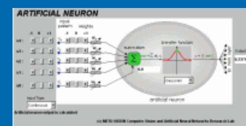
- I/ps ⇔ Electrical signals received at dendrites
  - Amplitude ⇔ Amount of Neurotransmitters 🡐 Pulse Frequency
    - + ⇔ Excitory & - ⇔ inhibitory
- Weights ⇔ Synaptic strength
  Dendrite receptors
- θ ⇔ Resting Potential
  - $\theta < 0$ always in neuron
- Activation ⇔ Sum of all synaptic excitations + resting potential
- Activation Function ⇔ Voltage gated Na Channel Threshold function
- O/p ⇔ Action potential initiation/repression at axon hillock

Artificial Neuron Abstraction

- McCulloch-Pitts Model – Formulation
  - Activation 
  - Augmented weights 
    - u0=1 & w0= θ
  - Vector Notation 
  - O/p function
    - Threshold  
    - Ramp  
    - Sigmoid $f(a) = \frac{1}{1+e^{-\lambda a}}$ 

Artificial Neuron Abstraction

- McCulloch-Pitts Model – Example
  - 4 I/p neuron →

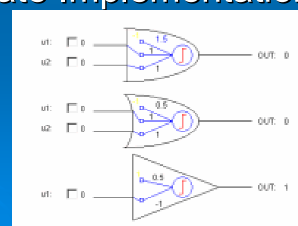


- McCulloch-Pitts – Logic Gate Implementation

1	0	1
0	0	0
AND	0	1

1	1	1
0	0	1
OR	0	1

1	1	0
0	1	0
NOT	0	1

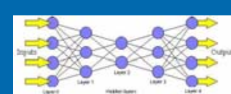


  - XOR? –linear separation!

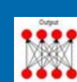
1	1	0
0	0	1
XOR	0	1

Neural Network Types

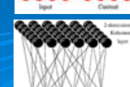
- Feedforward
  - (Multicategory) Perceptron
  - Multilayer – Error Backpropagation



- Competitive
  - Hemming
  - Maxnet



- Variations of Competitive
  - Adaptive Resonance Theory (ART)
  - Kohonen



- Hopfield

Hopfield Networks

- First developed by John Hopfield in 1982
- Content-Addressable Memory
- Pattern recognizer
- Two Types: Discrete and Continuous
- Common Properties:
  - Every neuron is connected to every other neuron. Output of neuron i is weighted with weight w_{ij} when it goes to neuron j.
  - Symmetric weights: $w_{ij} = w_{ji}$
  - No self-loops: $w_{ii} = 0$
  - Each neuron has a single input from the outside world

Discrete Hopfield Network: Training / Initalization

- Training: (Storing bipolar patterns)
  - Simultaneous, Single-step
  - Patterns: $s(p) = \{s_1(p), s_2(p), \ldots, s_n(p)\}$
  - Weight Matrix $W = \{w_{ij}\}$

$$T_{ij} = \sum_p s_i(p) * s_j(p) \quad for\ i \neq j$$

Fausett, Laurene. *Fundamentals of Neural Networks: Architectures, Algorithms and Applications*. Prentice Hall, Englewood Cliffs, NJ, 1994.

Discrete Hopfield Networks: Execution / Pattern Recall

- Asynchronous update of neurons
  - Neurons are updated sequentially at random
- Compute net input: $V\_in_i = I_i + \sum_j V_j * T_{ji}$
- Determine activation/output:

$$V_i = \begin{cases} 1 \ \ if\ V\_in_i > \theta_i \\ V_i \ \ if\ V\_in_i == \theta \\ 0 \ \ if\ V\_in_i < \theta_i \end{cases}$$

- Broadcast output V_i to all other neurons.

Hopfield, J.J."Neurons with graded response have collective computational Properties like those of two-state neurons" in Proc.Natl.Acad.Sci, USA. Vol.81, pp3088-3092

Discrete Hopfield Network

- Binary Hopfield Network Demo:

http://www.techhouse.org/~dmorris/JOHN/StinterNet.html

Discrete Hopfield Networks: Proof of Convergence

- Output of neuron i:

$$V_i = \begin{cases} 1 \ \text{if} \ \sum_{j \neq i} T_{ij} V_j > \theta_i \\ V_i \ \text{if} \ \sum_{j \neq i} T_{ij} V_j == \theta_i \\ 0 \ \text{if} \ \sum_{j \neq i} T_{ij} V_j < \theta_i \end{cases}$$

- Consider the following Energy function:

$$E = -\frac{1}{2} \sum_j \sum_{i \neq j} T_{ij} V_i V_j - \sum_i I_i V_i + \sum_i \theta_i V_i$$

This implies...

$$\Delta E = -\left[\sum_{i \neq j} T_{ij} V_i + I_i - \theta_i \right] [\Delta V_i] \leq 0$$

because [] *always has the same sign*

Hopfield, J.J."Neurons with graded response have collective computational Properties like those of two-state neurons" in Proc.Natl.Acad.Sci, USA. Vol.81, pp3088-3092

Discrete Hopfield Networks: Proof of Convergence (2)

- Furthermore, the energy function is bounded…since T_{ij}'s are all fixed, V_i is either V_0 or V_1 (typically 1 or 0), and Θ_i's are also fixed.

$$E = -\frac{1}{2} \sum_j \sum_{i \neq j} T_{ij} V_i V_j - \sum_i I_i V_i + \sum_i \theta_i V_i$$

- Since ΔE<=0 and E is bounded, the system must eventually settle down at a local or global minimum in terms of E.

Continuous Hopfield Networks

- Continuous values for neuron states and outputs instead of discrete binary or bipolar values.
- Simultaneous update instead of serial asynchronous update of discrete network
- Chemical system can emulate continuous hopfield nets

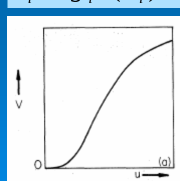
Continuous Hopfield Networks How do they work?

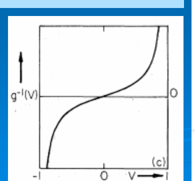
- Can be modeled as the following electrical system:

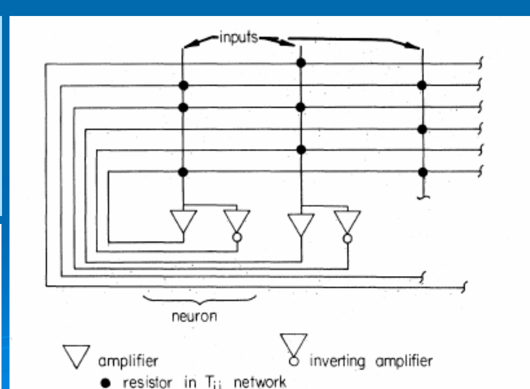
$$C\left(\frac{dv}{dt}\right) = \frac{dQ}{dt} = I$$

$$C_i\left(\frac{du_i}{dt}\right) = \sum_j T_{ij}V_j - \frac{u_i}{R_i} + I_i$$

$$u_i = g_i^{-1}(V_i)$$







Continuous Hopfield Networks Proof of Convergence

- Consider the following Energy Function:

$$E = -\frac{1}{2}\sum_i \sum_j T_{ij} V_i V_j + \sum_i \frac{1}{R_i} \int_0^{V_i} g_i^{-1}(V)\,dV + \sum_i I_i V_i$$

- Its time derivative with a symmetric T:

$$\frac{dE}{dt} = -\sum_i \frac{dV_i}{dt}\left(\sum_j T_{ij} V_j - \frac{u_i}{R_i} + I_i\right)$$

Hopfield, J. J. "Neurons with graded response have collective computational properties like those of two-state neurons", Proceedings of the National Academy of Science, USA. Vol 81, pp. 3088-3092, May 1984, Biophysics.

Continuous Hopfield Networks Proof of Convergence

- The bracket inside the time derivative of the energy function is the same as that in the original function describing the system.

$$\frac{dE}{dt} = -\sum_i \frac{dV_i}{dt}\left(\sum_j T_{ij} V_j - \frac{u_i}{R_i} + I_i\right) \qquad C_i\left(\frac{du_i}{dt}\right) = \sum_j T_{ij} V_j - \frac{u_i}{R_i} + I_i$$

$$\frac{dE}{dt} = -\sum C_i\left(\frac{dV_i}{dt}\right)\left(\frac{du_i}{dt}\right)$$

$$= -\sum C_i g_i^{-1'}(V_i)\left(\frac{dV_i}{dt}\right)^2 \le 0, \frac{dE}{dt} = 0 \;\Rightarrow \frac{dVi}{dt} = 0 \;\; for\ \forall\ i$$

Hopfield, J. J. "Neurons with graded response have collective computational properties like those of two-state neurons", Proceedings of the National Academy of Science, USA. Vol 81, pp. 3088-3092, May 1984, Biophysics.

Chemical Implementation of Neural Networks

- Single Chemical Neuron i:
  - $I^*_{1i}+C_i \leftarrow\rightarrow X_{1i} + C_i$ $\quad J_{1i}=k_1C_i-k_{\_1}C_iK_{1i}$
  - $X_{1i}+B_i\leftarrow\rightarrow X^*_{2i}+A_i$ $\quad J_{2i}=k_2X_{1i}Bi-k\_2Ai$
- Ci is the Input
- Ai + Bi = constant
  - Ai is high, Bi is low if Ci is above threshold
  - Bi is high, Ai is low if Ci is below threshold

Hjelmfelt, Allen, etal. "Chemical Implementation of neural networks and Turing machines" Proceedings of the National Academy of Science, USA. Vol 88, pp10983-10987, Dec. 1991

Chemical Implementation of Neural Networks

- Construction of Interneuronal Connections:
  - Species A_i and B_i may affect the concentration of the catalyst C_j of other neurons

$$C_j = \sum_k C_{jk}$$

- Each neuron uses a different set of chemicals and occupy the same container
  - Similar to logic networks using gene networks

Chemical Implementation of Neural Networks: AND gate

- Ai and Aj are output

Computing with Action Potential Timing

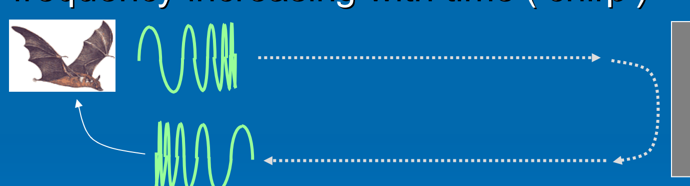
- [Alternative to Neural Network Communication Model]
- Neurons communicate with action potentials→
- Engineering models for neuron activity use continuous variables to represent neural activity
  - Activity → <rate of action potential generation>
- Traditional neurobiology: same model→
  - "short term mean firing rate"
- Average pulse rate is inefficient in neurobiology
  - Single neuron→ Wait for several pulses → slow
  - Multiple equivalent neurons→ average over → redundant 'wetware' & error

Action Potential Timing

- New examples in Biology:
  - Information → Timing of action potentials (Rather than pulse rate)
    - Ex: Moustache Bat
      - Uses timing to discriminate its sonar from environmental noise
    - Application: Analog match of odour identification
      - Solved more efficiently using action potential timing

Action Potential Timing

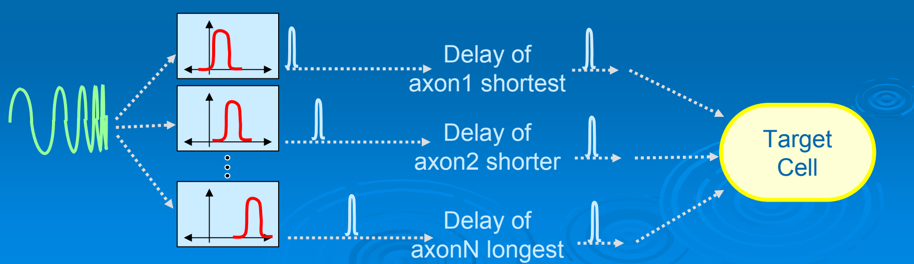
- Moustache Bat Sonar:
  - Generates 10 ms ultrasonic pulse with frequency increasing with time ('chirp')



  - Chirp is received back in cochlea

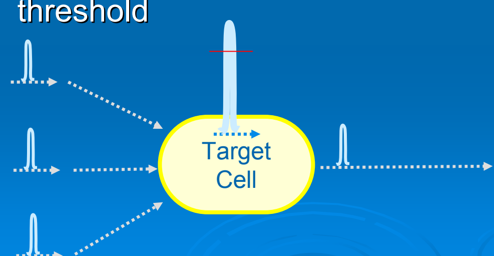
Action Potential Timing

- Moustache Bat Sonar:
  - In cochlea, cells with different freq. Selectivity (Filter bank)
    - Produce a single action potential if signal is within the pass-band
    - No action potential otherwise
      - Sequential response to different frequencies



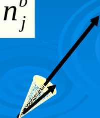
Action Potential Timing

- Moustache Bat Sonar:
  - Pulses leave cochlea cells in order
  - Length and propagation speeds of axons different → all pulses arrive at target cell simultaneously
  - High aggregate action potential at target cell reaches threshold



Action Potential Timing

- Analog match
  - Odour → Mixture of molecules with different concentrations: N_i $odour\_b : \bigcup_i N_i^b$
  - Matching odour
    - Intensity () varies
    - Concentration ratios similar
      - → normalized concentrations n_i similar: (λ: intensity) $n_i^b = \dfrac{N_i^b}{\lambda\left(=\sum_j N_j^b\right)}$
  - Analog match:
    - Whether stimulus, s, has the similar concentration ratios of constituents to a prescribed target ratio $n_1:\ldots:n_i:\ldots n_k$
    - Formulation: $\exists \lambda : \forall N_j \in s; N_j^s \approx \lambda \bullet n_j^b$
    - Conceptually:
      - Similarity of ratios (N1:N2:…:Nk)
      - Similarity of vector direction



Action Potential Timing

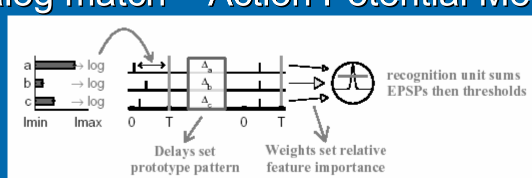
- Analog Match – Neural network implementation:
  - Unknown odour vector **I:** [I1 I2 …Ik]
    - Check if matches $normalized\_odour\_b : \bigcup_i \{n_i^b\}$
  - Target odour vector n: $n = \begin{bmatrix} n_1 \\ n_2 \\ : \\ n_k \end{bmatrix}$
  - Define weight vector W: $W = \dfrac{n}{\|n\|}$
  - Normalize I to unit length vector: $I_{norm} = \dfrac{I}{\|I\|}$
  - Recognition: $\vec{I}_{norm} \bullet \vec{W} > threshold\,(i.e.\ 0.95)$
    - Result of inner product→
      - $\cos(I_{norm}, W)$ → [-1,1]; actually [0,1] as both vectors in 1st quadrant (concentrations > 0)
      - Closer to 1 → vectors align better

Action Potential Timing

- Analog Match – Neural network implementation:
  - 4 weaknesses:
    - Euclidean normalization expensive
    - If weak component (in conc.) has importance or strong is unreliable, we cannot represent this – weights describe only concentration of comp-s
      - We can have 'weighted' weights
[w1]: conc. Ratios & [w2]: priorities➔ W=w1.*w2
    - No Hierarchical design → normalization problem
    - No tolerance to missing i/ps or highly wrong i/ps
      - I.e. n1:n2:n3:n4:n5 1:7:1.5:0.4:0.1 (/10)
-> {I1,I2,I3,I4,I5}: {1, 0, 1.5, 0.4, 0.1}
-> {I1,I2,I3,I4,I5}: {1, 7, 9, 0.4, 0.1}

Action Potential Timing

- Analog match – Action Potential Method



  - 3 i/ps Ia,Ib,Ic → log(Ix) define advance before reference time T
  - Target odour in [n] → $n = \begin{bmatrix} n_a \\ n_b \\ n_c \end{bmatrix}$
    - Delays: $\Delta_j = \log(n_j)$
      - ! [n] should be upscaled to have $n_i > 1$ (o/w advancer!)
  - Analog Match ➔
All pulses arrive at target simultaneously
    - Scaling doesn't change relative timing – all shift
$\log(\lambda \bullet I_x) = \log(I_x) + \log(\lambda)$

Action Potential Timing

- Analog match – Action Potential Method
  - Ex:

$$n = \begin{bmatrix} n_a \\ n_b \\ n_c \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \Rightarrow \begin{matrix} \Delta_a = \log(n_a) = 0 \\ \Delta_b = \log(n_b) = 0.31 \\ \Delta_c = \log(n_c) = 0.48 \end{matrix}$$

$$I = [I_a \quad I_b \quad I_c] = [10 \quad 20 \quad 30] \Rightarrow \textit{Perfect} \quad \textit{Match}$$

$$\log(I) = [1 \quad 1.31 \quad 1.48] \Rightarrow$$

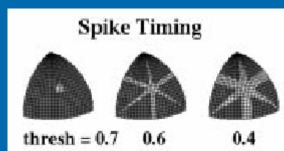
$$\left| \begin{matrix} I_a \quad \textit{starts} \quad \textit{at}: \quad T-1 \\ I_b \quad \textit{starts} \quad \textit{at}: \quad T-1.31 \\ I_c \quad \textit{starts} \quad \textit{at}: \quad T-1.48 \end{matrix} \right\rangle \begin{matrix} I_a \quad \textit{ends} \quad \textit{at}: \quad T-1+0 = T-1 \\ I_b \quad \textit{ends} \quad \textit{at}: \quad T-1.31+0.31 = T-1 \\ I_c \quad \textit{ends} \quad \textit{at}: \quad T-1.48+0.48 = T-1 \end{matrix}$$

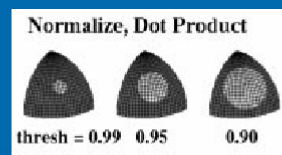
Action Potential Timing

- Analog match – Action Potential Method
  - All 4 weaknesses removed
  - (1) No normalization required
  - (2) Pulse advances w.r.t. T
    → concentration/scaling
    Synaptic Weights → importance
  - (3) Hierarchy can exist
    – all neurons independent
  - (4) Tolerates missing/grossly inaccurate info =>

Action Potential Timing

- Analog match
- Error Tolerance Comparison of 2 Methods:
  - Target = n = [1 1 1]'





  - Neural Net Model →
    The cone around [1 1 1] vector defines tolerance: projects a ~circle on unit circle
  - Action Potential Timing → makes bisectors → star shape
    Finds individual scalings: pulses with same scaling overlap
  - Received I/p = I = [1 1 0]→
    - Neural net needs to accept almost every i/p
    - Action potential timing detects similarity

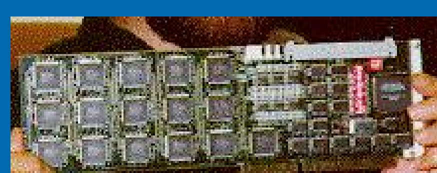
Action Potential Timing

- Analog match – Action Potential Method
  - Reference Time T
    - Reference time T known by all neurons
      - Externally generated → bat example
      - Internally generated periodically

Neural Network Hardware: TOTEM

- Developed by

Neural Network Hardware: IBM ZISC



Index of Terms

- Perikaryon: body of a nerve cell as distinguished from the nucleus, axon, and dendrites

Back

- axon hillock: a specialized region of the soma called the axon hillock where the action potential is initiated once a critical threshold is reached

Back

- terminal buttons: The larger ends of axons at the synapse, where the neurotransmitters are released – same as presynaptic terminals

Back

Index of Terms

- Ion channels : specialized cellular devices that can transport ions in and out of the cell thru the membrane

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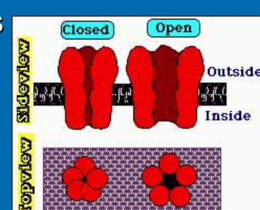

  - Nongated channels are always open and are not influenced significantly by extrinsic factors
  - Gated channels open and close in response to specific electrical, mechanical, or chemical signals

Back

- Neurotransmitters: small molecules that are liberated by a presynaptic neuron into the synaptic cleft and cause a change in the postsynaptic membrane potential

Back

Index of Terms

- Depolarization : Reduction of membrane charge separation = Increase in Membrane potential (less negative)

Back

- Hyperpolarization : Increase in membrane charge separation = Decrease in Membrane potential (more negative)

Back

- Neurotransmitters: small molecules that are liberated by a presynaptic neuron into the synaptic cleft and cause a change in the postsynaptic membrane potential

Back