Computational Neuroscience

1. Introduction
2. Current Issues: Neural Coding

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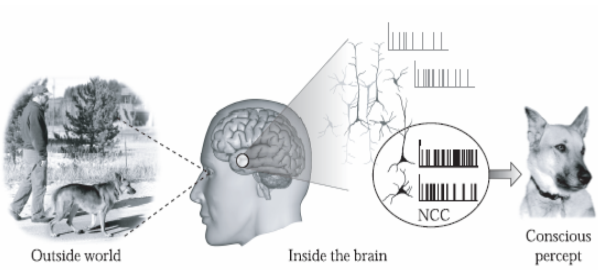
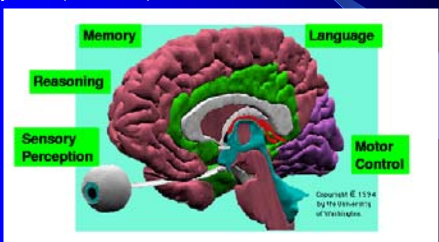


Koch, C. (2003), *The Quest for Consciousness: A Neurobiological Approach*, Roberts & Co Publishers.

What is Neuroinformatics/ Computational Neuroscience?

- Challenge: Understanding of the human nervous system (the brain)



- It has been proved very difficult to build machines with cognitive capabilities matching our own

What is Neuroinformatics/ Computational Neuroscience?

- Brain abilities:
  - perception
  - decision making
  - cognition
  - reasoning
- Learning from the brain and learning about the brain by studying information processing in the brain

What is Neuroinformatics/ Computational Neuroscience?

- Disciplines involved:
  - *Neuroscience-related life sciences*: neuroscience, neurobiology, biology, psychology, linguistics
  - *Information sciences and related*: computer science, mathematics, statistics, physics and electronic engineering
  - *Humanities*: philosophy

Neuroinformatics/Computational Neuroscience: INTERDISCIPLINARY

What is Neuroinformatics/ Computational Neuroscience?

Neuroinformatics/Computational Neuroscience is concerned with:

- **developing and applying *computational methods* to the study of brain and behaviour**;
- applying advanced IT methods to deal with the huge quantity and great complexity of neuroscientific data;
- exploiting our insights into the principles underlying brain function to develop new IT technologies.

Developing and applying computational methods to the study of brain and behaviour:

- How? By building computational quantitative models to model what the brain does in terms of *computations*; thus we will try and understand the brain as a *computing device*
- The lecture will introduce the basic concepts of this area and concentrate on the current issue of neural coding

Developing and applying computational methods to the study of brain and behaviour:

How? By building computational quantitative models to model what the brain does in terms of *computations*; thus we will try and understand the brain as a *computing device*

Why do we need models?

• Force one to make assumptions explicit; cannot get very far with hypotheses expressed in intuitive terms. e.g., ``visual experience affects visual development''

• Enables many "virtual" experiments to be done
⇒ can pinpoint the one that is most crucial

• Can lead to unexpected predictions

• Often much quicker/easier to try out ideas and so it can guide potential experiments

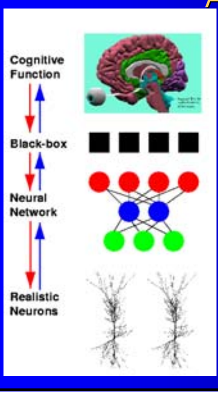
Who could attend this lecture

- ***Computer Scientists*** who want to learn about the brain and modelling it: no prior neuroscience background required
- ***Neuroscientists*** who want a computational perspective: focus on representations and algorithms rather than anatomy and physiology; good to have a close contact with them so as to build good models
- ***Cognitive scientists*** who want to know more about brains as information processing devices: taking the "brain as computer" metaphor seriously, requires learning as much as possible about both

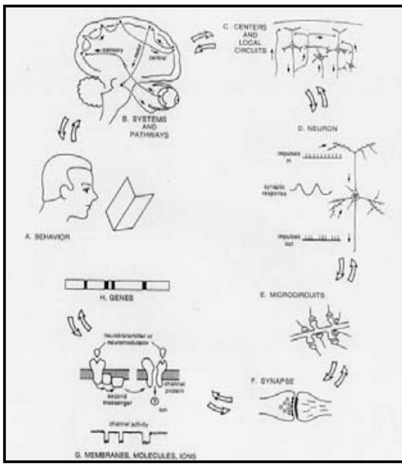
Sources

- **Typical journals**:
  Neural Computation
  Journal of Computational Neuroscience
  Biological Cybernetics
  and occasional articles in many other journals including:
  Neural Networks
  IEEE Transactions on Neural Networks
- **Typical Conferences:**
  CNS (Computational Neuroscience Meeting)
  NIPS (Neural Information Processing Systems)
  NCWS (Neural Coding Workshop)
  NCPW (Neural Computation and Psychology Workshop)
  Neurosciences Meeting

Understanding Cognition: A Multilevel Approach



- computational description of cognitive function
- algorithmic description, probably involving multiple, interacting computational modules
- neurally-relevant implementation with artificial neural networks
- implementation mapped directly to the biological neural systems.

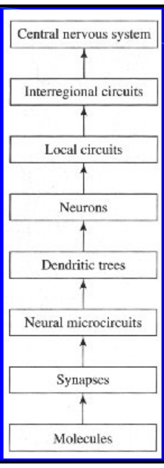


INVESTIGATE ALL LEVELS

• Need to understand the behaviours we are capable of (psychologists)

• Molecular Biology elucidates neuronal functioning at molecular level

• *In this lecture*: Neuronal level

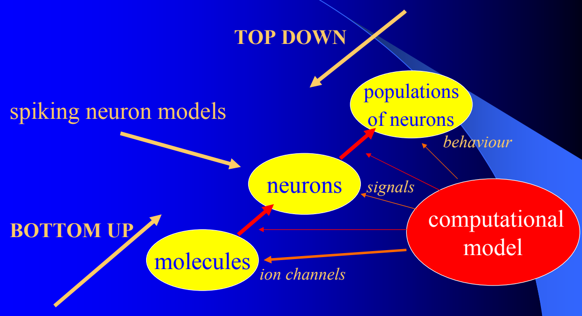


Major functional computing components of the brain are:

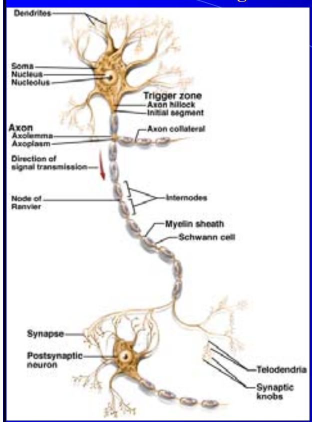
1. **synapses**: points of connection between two neurons
2. **microcircuits**: interactions between nearby synapses onto a single neuron
3. **neurons**: the fundamental computing units of the nervous system
4. **local circuits**: small networks of nearby neurons

Genetics and molecular biology underlie these components. Cognitive function results from the feed forward and feedback interaction of local circuits to and form functional modules, systems and pathways.

Neurobiological Modelling



Schematic diagram of biological neurons



* the dendrites and the axon make *synaptic contacts* with dendrites of other neurons
* synapse is *directional*
* Information enters the neuron at the synapses on the dendrites

Transmission of signals

1. Chemical known as neurotransmitter released from synaptic vesicles
2. Causes an electrical charge (*action potential*) which can raise or lower its potential depending on whether the synapse is excitatory or inhibitory
3. If the total potential reaches a *threshold*, an *action potential* or *spike* is transmitted down the axon (starting at the *axon hillock*)
4. After firing, the cell has to wait for a *refractory period* before it can fire again.

Levels of Single Neuron Modelling

- Many different types of single neuron models: from very abstract and simple to very realistic and complicated:
  - Binary threshold unit (McCulloch and Pitts)
  - Continuous unit
  - Integrate-and-fire (continuous in time)
  - Spiking
  - A few compartments
  - Many compartments
  - Individual channels
  - Detailed model of channel dynamics
  - etc
- All models must make simplifications to be useful
- Which one to use, is dependent on the purpose

Simple Models: Integrate and Fire neuron models

• Simplified neuron models where the biophysical mechanisms are not explicitly modelled (like in the Hodgkin & Huxley, 1952 model)
- simulations can be accelerated

Integrate and Fire models

* An action potential (AP) occurs whenever the membrane potential of the model neuron exceeds a threshold value

* After the action potential, the membrane potential resets to the reset potential, below the threshold.

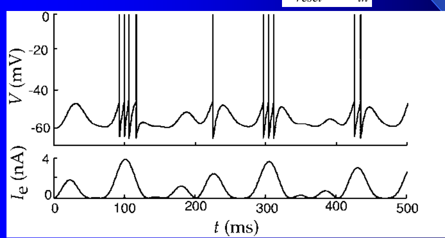
Basic equation for the leaky integrate-and-fire model:

$$\tau_m \frac{dV(t)}{dt} = E_L - V(t) + R_m I_e(t)$$

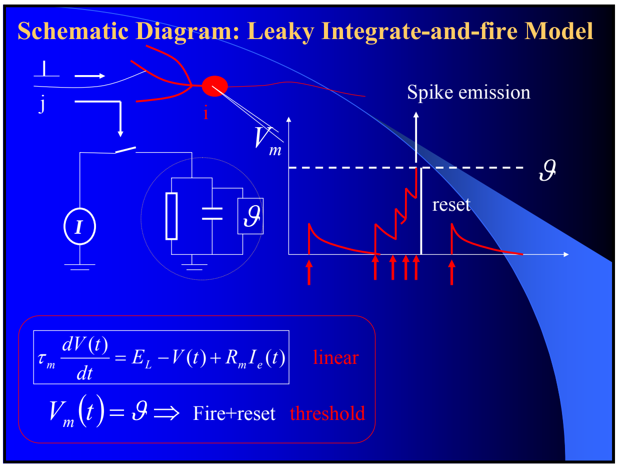
Model assumptions – generation of spikes:

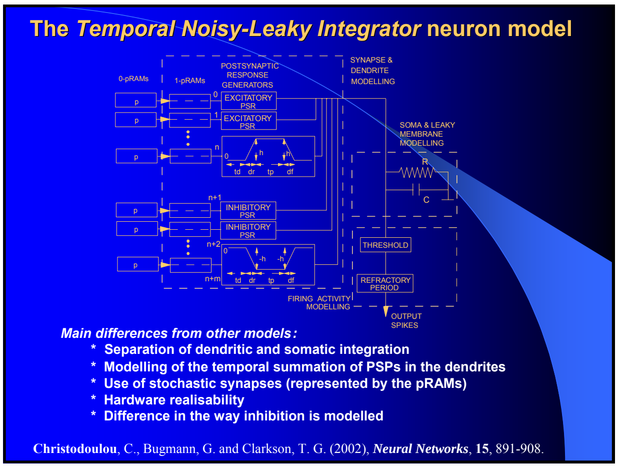
Fire a spike if: $V_m(t) = V_{th}$

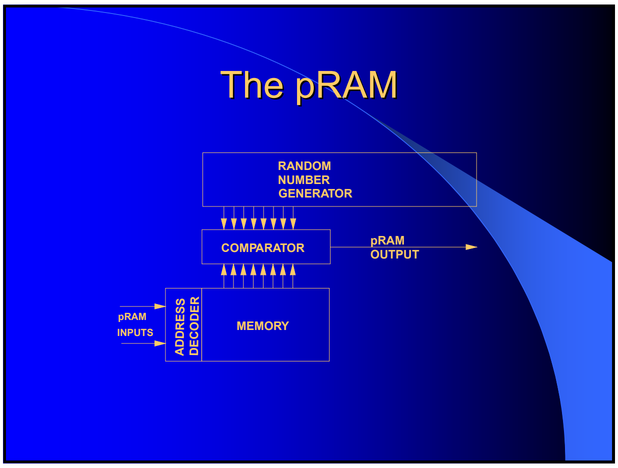
and reset the membrane potential $V_{reset} < V_{th}$

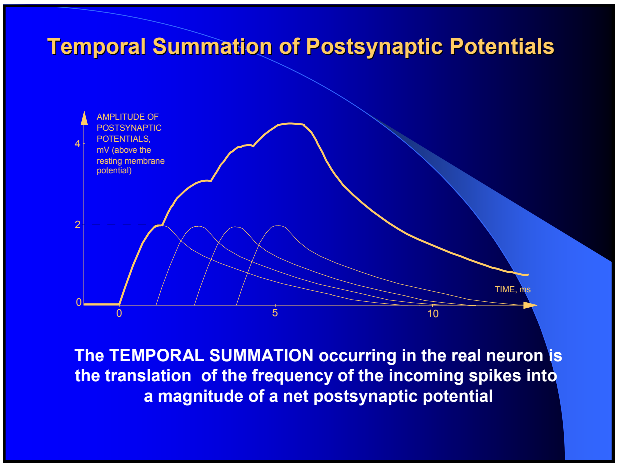


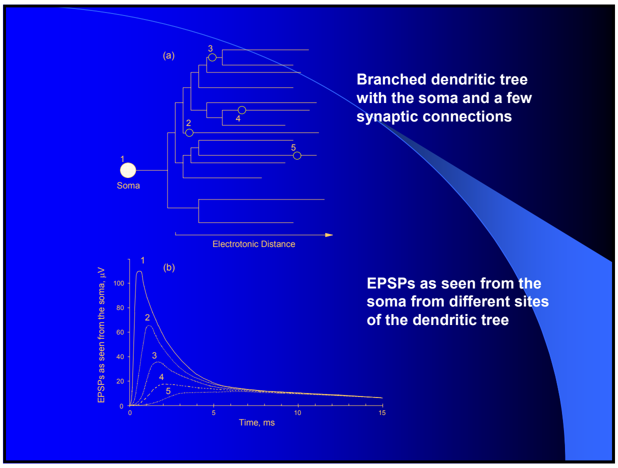
Leaky integrate-and-fire model driven by a time-varying current

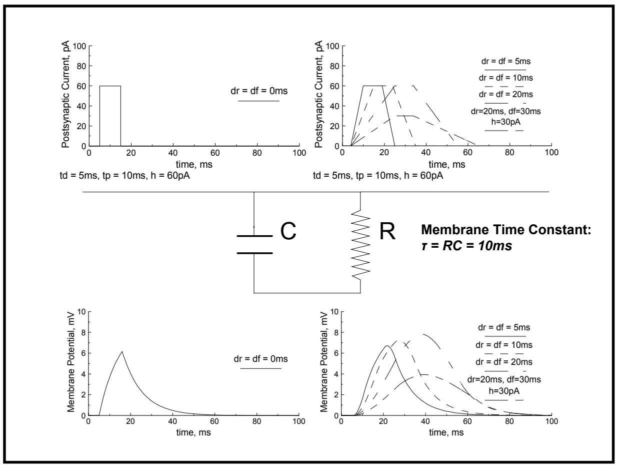

Schematic Diagram: Leaky Integrate-and-fire Model
Spike emission
reset
$\tau_m \frac{dV(t)}{dt} = E_L - V(t) + R_m I_e(t)$
linear
$V_m(t) = \vartheta \Rightarrow$ Fire+reset
threshold


The *Temporal Noisy-Leaky Integrator* neuron model
POSTSYNAPTIC RESPONSE GENERATORS
SYNAPSE & DENDRITE MODELLING
EXCITATORY PSR
INHIBITORY PSR
SOMA & LEAKY MEMBRANE MODELLING
THRESHOLD
REFRACTORY PERIOD
FIRING ACTIVITY MODELLING
OUTPUT SPIKES
Main differences from other models:
* Separation of dendritic and somatic integration
* Modelling of the temporal summation of PSPs in the dendrites
* Use of stochastic synapses (represented by the pRAMs)
* Hardware realisability
* Difference in the way inhibition is modelled
Christodoulou, C., Bugmann, G. and Clarkson, T. G. (2002), *Neural Networks*, 15, 891-908.


The pRAM
RANDOM NUMBER GENERATOR
COMPARATOR
pRAM OUTPUT
pRAM INPUTS
ADDRESS DECODER
MEMORY


Temporal Summation of Postsynaptic Potentials
AMPLITUDE OF POSTSYNAPTIC POTENTIALS, mV (above the resting membrane potential)
TIME, ms
The TEMPORAL SUMMATION occurring in the real neuron is the translation of the frequency of the incoming spikes into a magnitude of a net postsynaptic potential

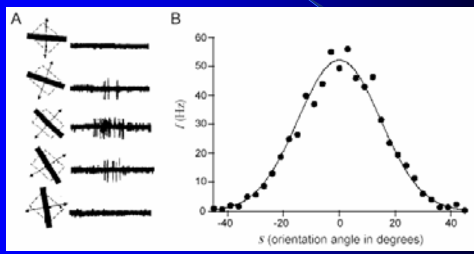

Branched dendritic tree with the soma and a few synaptic connections
Soma
Electrotonic Distance
EPSPs as seen from the soma from different sites of the dendritic tree
Time, ms


Postsynaptic Current, pA
time, ms
dr = df = 0ms
td = 5ms, tp = 10ms, h = 60pA
dr = df = 5ms
dr = df = 10ms
dr = df = 20ms
dr=20ms, df=30ms
h=30pA
C
R
Membrane Time Constant:
τ = RC = 10ms
Membrane Potential, mV

Neural Coding

Neural coding: firing rates depend on stimulus

Visual cortical neuron: variation with orientation of stimulus (unconscious animal)



Spike trains as a function of bar orientation

Gaussian tuning curve

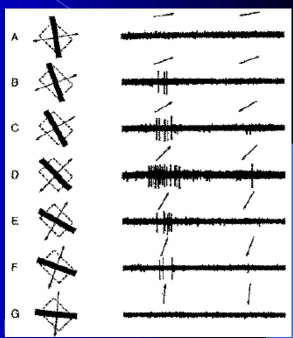
Hubel DH & Wiesel TN (1962). *Journal of Physiology* **160**:106-154.
Hubel, DH & Weisel, TN (1968). *Journal of Physiology* **195**:215-243.

Neural coding: firing rates depend on stimulus

Orientation and Direction Selectivity

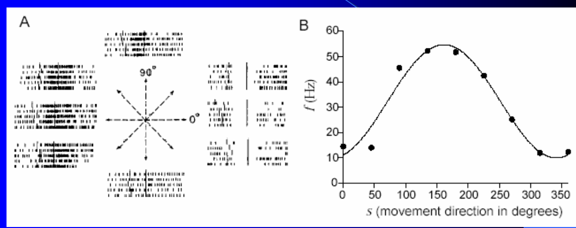
www.shadlen.org/~mike/movies/

1. Direction Selective.mov
2. Orientation Selective.mov



Neural coding: firing rates depend on stimulus

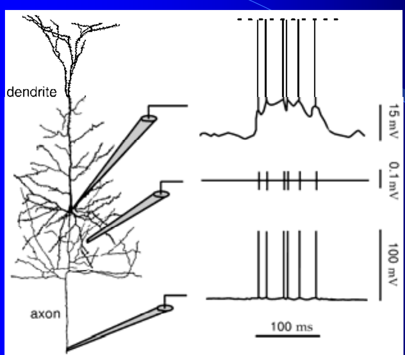
Motor cortical neuron: variation with direction of movement (conscious animal)



Spike trains as a function of hand reaching direction

Cosine tuning curve

Recording the Output of a Neuron



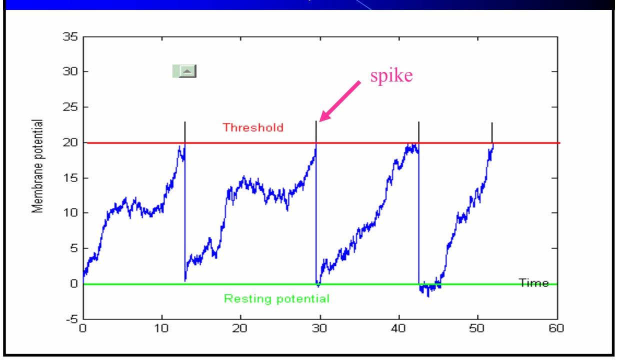
Intracellular Recording at the Soma

Extracellular Recording near the Soma

Intracellular Recording at the Axon

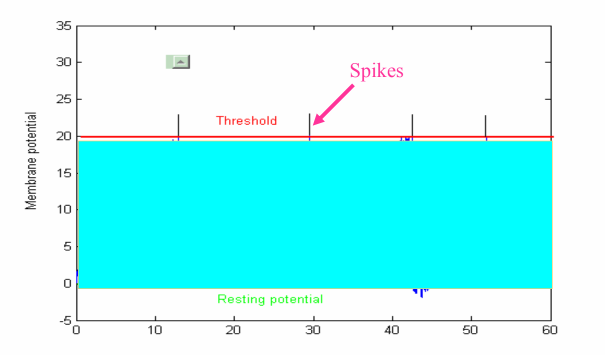
Single neuron activity

If you measure the *membrane potential* of a neuron and print it out on the screen, it looks like:



Abstraction

So we can forget all sub-threshold activity and concentrate on *spikes (action potentials)*, which are the signals sent to other neurons

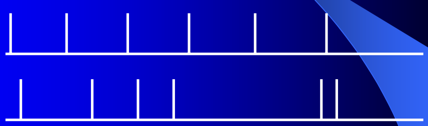


- Only spikes are important since other neurons receive them (signals)
- Neurons communicate with spikes
- Information is *coded* by spikes

Firing Rate

Since the rate of spiking indicates synaptic activity, one could use the firing rate as the information in the network

However APs are all-or-nothing and spike timing is stochastic



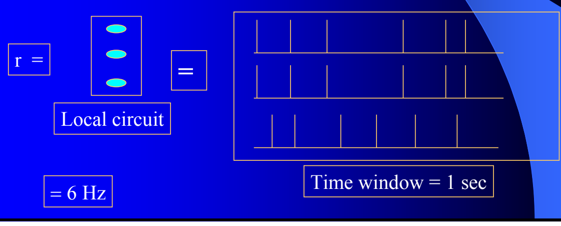
With identical input
for the identical neuron

spike patterns are similar, but not identical

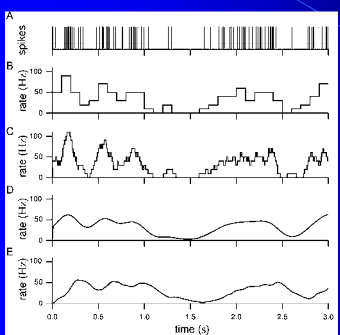
- Single spiking time is meaningless
- To extract useful information, we have to average

✓ for a group of neurons in a local circuit where neuron codes the same information
✓ over a time window

to obtain the firing rate *r*



Computing the Firing Rate of a Neuron



Extracellular spike train

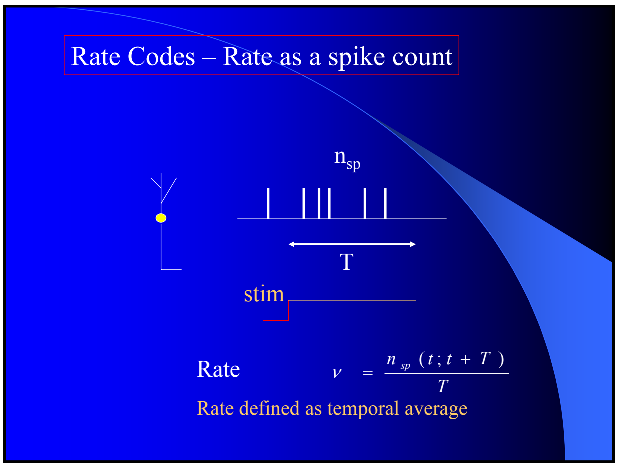
Rectangular Window (100 ms)

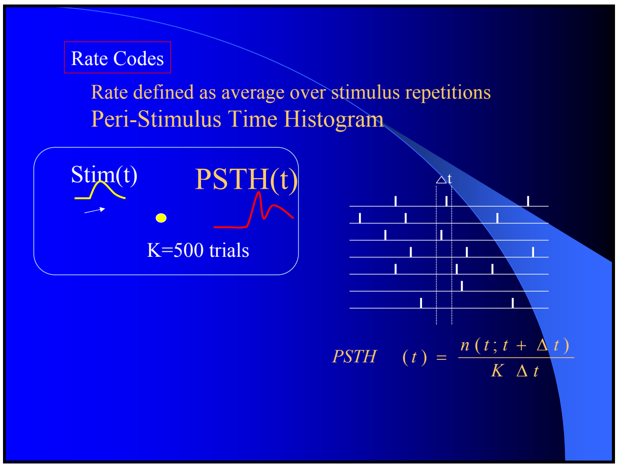
Sliding Window (100 ms)

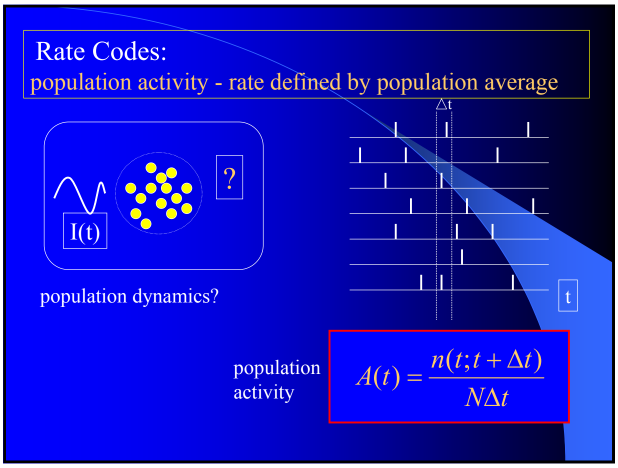
Gaussian Window (σ = 100 ms)

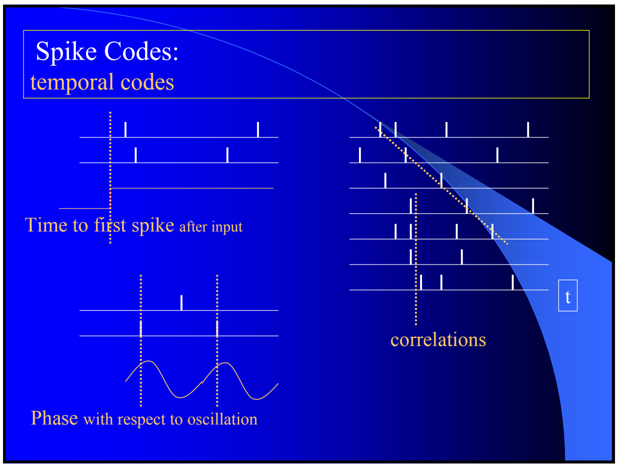
Causal Window ($1/\alpha$ = 100 ms)

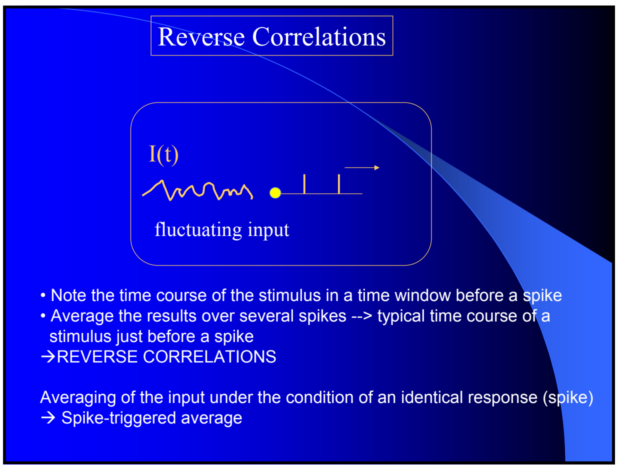
Rate Codes
vs
Spike (or temporal) codes

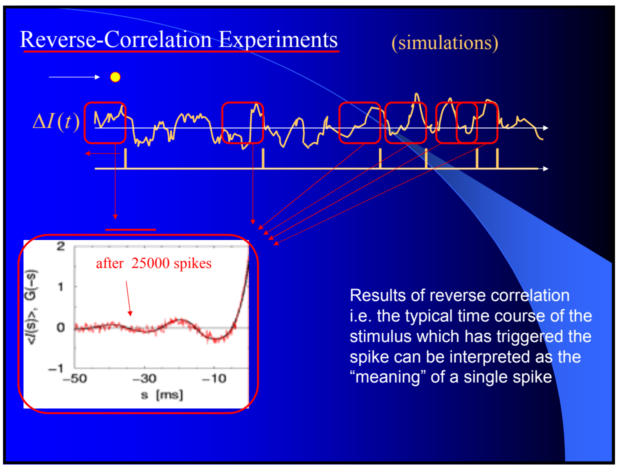

Rate Codes – Rate as a spike count
n sp
T
stim
Rate
ν = n sp (t; t + T) / T
Rate defined as temporal average


Rate Codes
Rate defined as average over stimulus repetitions
Peri-Stimulus Time Histogram
Stim(t)
PSTH(t)
K=500 trials
Δt
PSTH (t) = n(t; t + Δt) / K Δt


Rate Codes:
population activity - rate defined by population average
I(t)
?
population dynamics?
Δt
t
population activity
A(t) = n(t;t+Δt) / NΔt

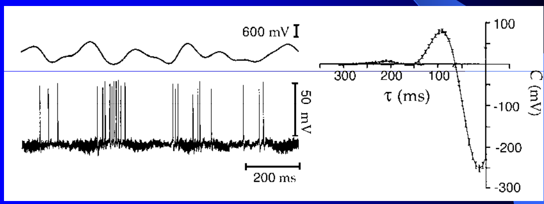

Spike Codes:
temporal codes
Time to first spike after input
t
correlations
Phase with respect to oscillation


Reverse Correlations
I(t)
fluctuating input
• Note the time course of the stimulus in a time window before a spike
• Average the results over several spikes --> typical time course of a stimulus just before a spike
→REVERSE CORRELATIONS
Averaging of the input under the condition of an identical response (spike)
→ Spike-triggered average


Reverse-Correlation Experiments
(simulations)
ΔI(t)
after 25000 spikes
<I(s)>, G(-s)
2
1
0
-1
-50
-30
-10
s [ms]
Results of reverse correlation
i.e. the typical time course of the stimulus which has triggered the spike can be interpreted as the "meaning" of a single spike

Examples of reverse correlation

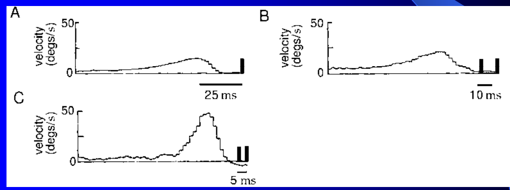
Electric sensory neuron in electric fish:
Stimulus = fluctuating potential (generates electric field)



Examples of reverse correlation

Motion-sensitive neuron in blowfly visual system:
Stimulus (t) = velocity of moving pattern in visual field

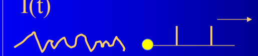
Spike Triggered Average



2-Spike Triggered Average (5 ms)

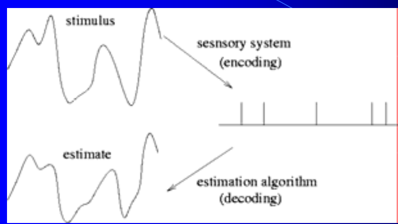
Stimulus Reconstruction

I(t)



fluctuating input

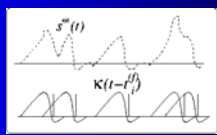
Stimulus Reconstruction



Encoding problem:
$P(\{t_i\} \mid s(t))$

Decoding problem:
$P(s(t) \mid \{t_i\})$

Bialek et al



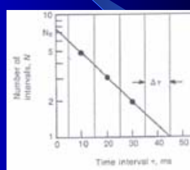
TYPES OF SPIKE TRAINS OBSERVED IN NEURONS

- **Completely Random**:
  Recorded in the visual cortex and the extrastriate cortex of cats
- **Bursty**:
  Definition: spike trains characterised by clusters of short intervals interspersed between irregular long intervals
  Recorded in the ventrolateral nucleus of the thalamus of a sleeping cat; in the motor cortex of a conscious cat; in rat hippocampal pyramidal cells
  Importance: burst arrival time might play a role in temporal coding; recorded bursts in a locust contribute to the generation of flight motor pattern
- **Regular:**
  At extremely high firing rates approaching 1/(refractory period)

Characterisation of stochastic neuronal firing properties and analysis of spike trains

INTERSPIKE INTERVAL (ISI) DISTRIBUTION

Example of a spontaneous neuron discharge obeying a Poisson process



ISI histogram distribution using bins of Δt = 10ms wide

Modelling spike trains

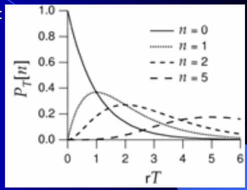
- **Point process**: stochastic process that generates a sequence of events (in general, P(event)) can depend of the entire history of the preceding events
- **Renewal process**: point process, where P(event) depends only on the immediately preceding event (intervals of successive events are independent
- **Poisson process**: point process, where P(event) is *independent* of preceding events.

Poisson distribution

Homogeneous Poisson process: r = rate = prob of firing per unit time, i.e., $r\Delta t$ = prob of spike in interval $[t, t+\Delta t]$ $(\Delta t \to 0)$

Probability of n spikes in interval of duration T:

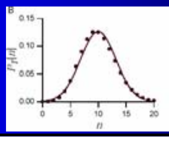
$$P_T(n) = \frac{(rT)^n}{n!} e^{-rT}$$



Mean count: $\bar{n} = rT$

variance: $\sigma_n^2 = \overline{(n - \bar{n})^2} = rT = \bar{n}$

large rT: → Gaussian



Fano factor

$$F = \frac{\overline{(n-\bar{n})^2}}{\bar{n}}$$ spike count variance / mean spike count

$F = 1$ for stationary Poisson process

Poisson process: interspike interval distribution

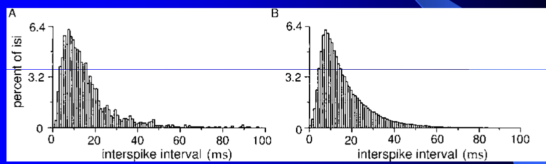
Exponential distribution: $P(t) = re^{-rt}$ (like radioactive Decay)

Mean Interspike Interval (ISI): $\bar{t} = \frac{1}{r}$

variance: $\overline{(t-\bar{t})^2} = \frac{1}{r^2} = \bar{t}^2$

ISI distribution to a real neuron

ISI distribution to a leaky I&F model with random inputs and a refractory period



Characterisation of stochastic neuronal firing properties and analysis of spike trains

Coefficient of Variation (C_V) of Interspike Intervals (ISIs): measure of spike train irregularity defined as the standard deviation ($\sigma_{\Delta t}$) divided by the mean ISI (Δt_M):

$$C_V = \sigma_{\Delta t} / \Delta t_M$$

** For a random pure Poisson process C_V = 1 and the ISI histogram distribution follows an exponential shape.

** **The C_V is a measure of the relative spread of the distribution and its deviation from exponentiality.**

** **Poisson-type firing is verified if the ISIs are both:**
(i) exponentially distributed and
(ii) independent

OTHER ISI DISTRIBUTION SHAPES

(i) **γ (gamma) Distribution:**
Denotes that spike trains lie somewhere between randomness and regularity

(ii) **Distribution with a sharp leading hump with long but flat & low tail:**
Indicates bursting behaviour

(iii) **Bimodal Distribution**
Reflects regular burst discharges

(iv) **Multimodal Distribution**
Needs to be assessed with other characteristics

Information Coding
Action Potential Timing vs. Frequency

How is information represented in the nervous system?

1. Several possible "codes" have been proposed over the decades
   - *rate codes* (continuous)
   - *temporal* or "*correlation*" *codes* (discrete)
   - *population codes* (can be rate- or temporal-based)
2. Temporal codes were the earliest proposed information representation fell out of favour as investigators focused on the amount of noise seemingly inherent in the brain - rate codes which could average out noise became vogue
3. Only in the last 10 years or so has temporal coding experienced a resurgence in popularity as we get a handle on the precision of individual neurons even in the presence of noise, as well as the seeming importance of neuronal synchronization and oscillations
4. Most likely, the Central Nervous System is as efficient as possible, taking advantage of multiple coding schemes to multiplex information

Information Coding
Temporal Codes

More complex but more efficient as opposed to *rate codes*

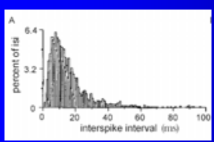
- As opposed to *rate codes* where the only variable of interest is the firing rate of a given neuron, a more complex set are the general group of *temporal codes* or *correlation codes*
- Spike doublets, triplets, and higher order combinations can carry information in the precise timing of their occurrences - presumably some delay-mechanism in the postsynaptic neuron can do the decoding
- Population-based temporal codes draw upon the specific timings of several streams of inputs (e.g. synchronous input) - presumably coincidence detection by the postsynaptic neuron performs the decoding
- Depends critically on the precision of cortical neurons in producing well-timed spikes despite a multitude of noisy contamination

Neural Code and identification of the determinants of the highly variable firing observed in neurons

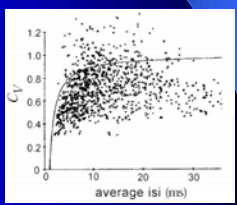
The `neural code` controversy - revitalised by Softky & Koch,1993 (S&K93):

Showed that firing in cortical neurons at high firing rates (up to 200Hz) when repeatedly stimulated with exactly the same visual stimulus is nearly consistent with a completely random process (Poisson-type).

ISI distribution



CVs for many neurons



Neural Code and identification of the determinants of the highly variable firing observed in neurons

* Using a leaky-integrator type neuron, they failed to reproduce the high variability observed in cortical cells at high firing rates.

* High firing variability could only be obtained at low firing rates or at high firing rates with unrealistically short membrane integration time constants.

* **Conclusion**:
The neural code is based on temporal precision of input spike trains, that is neurons behave as coincident detectors rather than leaky integrators.

Is the neural code based on rate encoding or is it based on precise processing of coincident presynaptic events?

The **rate encoding** principle which is based on temporal integration of input signals would imply that:
irregularity reflects noise

The **precise processing of coincident presynaptic events** principle would imply that:
irregularity does convey information

The problems:

1. **Which are the determinants of the highly variable firing observed in neurons?**
2. **How cortical neurons code information?**

Importance of solving the Neural Code problem

A solution would provide the basis for the analytical evaluation of the brain's information processing capability and would give us a further insight as to those problems which are essential to its functional organisation

Brief review of the most important attempts to model high firing variability & possible solutions to the neural code problem

Shadlen and Newsome, 1994 (S&N94), 1998:
Used a random walk model and a high rate of input signals and produced high irregular firing by **appropriate balancing of excitation and inhibition** on a single cell.
Conclusion: The ***neural code is based on rate encoding*** rather than coincidence detection.

Bell et. al., 1995:
Supported the ***coincidence detection principle*** & produced high variability with a single compartment Hodgkin & Huxley model with:
* **balanced excitation and inhibition** (with the balance point near the threshold in contrast with S&N94)
* **weak potassium current repolarisation** (corresponding to the degree of reset)
* **fast effective membrane time constant**.

Lin et al., 1998
Reproduced the results of S&K93 using **precise coupling in a network of I&F neurons** arranged in one-dimensional ring topology.
So: ** Dynamic network effects can indeed produce high C_Vs, BUT:
** When these network effects are examined in more realistic neural networks (e.g. Usher et al. 1994), they do not produce high variability in the high frequency range showed by S&K93.

Brief review… (continued)

Feng & Brown, 1998:
Showed using an I&F model that the C_V is an increasing function of the length of the distribution of the input inter-arrival times and the degree of balance between excitation and inhibition (r). For a range of r (excluding exact balance), C_V`s ε [0.5, 1].
Feng & Brown, 1999:
C_V`s ε [0.5, 1] can also be obtained with a leaky I&F model (Stein's model) with or without reversal potentials (when the attractor of the deterministic part of the dynamics is below the threshold and firing results from random fluctuations)
Brown et al., 1999:
Obtained C_V`s ε [0.5, 1] with H&H and FitzHugh-Nagumo neurons and random synaptic input, independent of the inhibitory input level.

Questions on the work of Feng & Brown:
(i) No clarification whether the C_V values they obtained are for high firing rates.
(ii) They only used the C_V statistic for demonstrating high variability; C_V`s ε [0.5, 1] are not equivalent with Poisson statistics.

Temporally correlated or uncorrelated inputs?
With temporally correlated inputs high firing variability can be achieved (Stevens & Zador, 1998; Sakai et al., 1999; Feng & Brown, 2000). However the assumption that inputs to cortical neurons are temporally correlated (or synchronous) is still to be convincingly proved. The correlation hypothesis may be valid for neurons in the auditory cortex where correlated inputs have been observed due to cochlear vibrations.

Observation:

The neural code question relates to the relative contribution on the high firing variability of:

- **the input current fluctuations, denoting coincidence detection and**
- **the temporal integration, denoting rate encoding**

A possible approach to the problem:

- **Using a realistic neuron model, reproduce the high firing variability of real neurons and identify the mechanisms of the model which this firing irregularity depends on.**
- **Examine which of the reported mechanisms of irregular firing is able to produce Poisson spike trains - the ones that do, are likely to reflect the firing mechanisms in real cells.**
- **Quantify the relative contribution of the input current fluctuations and temporal integration to the high firing variability.**

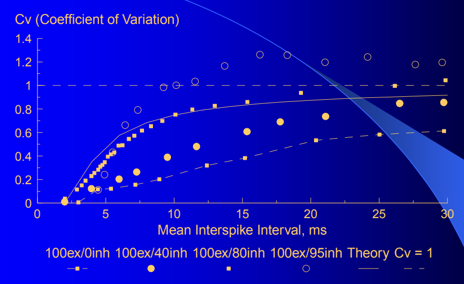
Note: Neurons may incorporate coding schemes based on a combination of rate and temporal coding

Our contribution to the debate:

Testing the effects on the high firing variability of:

- ***concurrent excitation and inhibition*** **(by using the TNLI neuron model)**
- ***partial somatic reset*** **(by using a simple Leaky Integrate & Fire neuron)**

Firing variability at different levels of inhibition (TNLI)

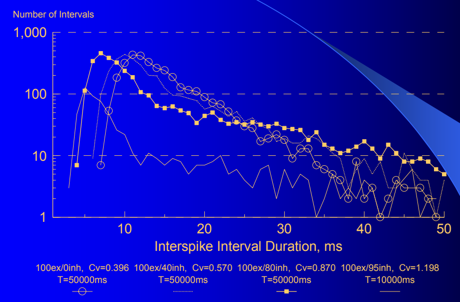


The theoretical curve for a random spike train with discrete time steps Δt and a refractory time of t_R is given by:

$$C_V(\Delta t_M) = \sqrt{\ [(\Delta t_M - t_R)/ \Delta t_M]},$$ where Δt_M is the mean ISI

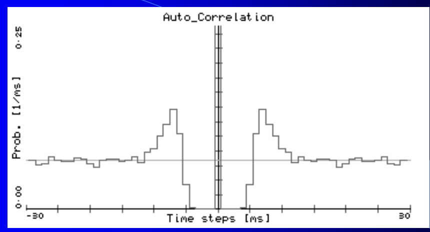
Christodoulou, C. and Bugmann, G. (2000). ***Biosystems***, **58**, 41-48.
Christodoulou, C., Bugmann, G. and Clarkson, T. G. (2002), ***Neural Networks***, **15**, 891-908.

Interspike Interval Histogram Distributions for different inhibition levels (Δt_M = 15ms)



- With 80% inhibition the distribution follows a Poisson tail
- Peak present because of clusters of short intervals

Autocorrelogram for the TNLI with inhibition at 80% of excitation



Δt_M = 15ms; t_R = 2ms; C_V = 0.87; time step = 1ms

- The curve shows a tendency for the model to produce pairs of spikes with intervals typically 7ms. These short bursts contribute to the high value of the C_V.
- The depletion on either side of the origin is due to t_R, indicating a reduced probability of firing.
- The fact that the curve is not flat indicates that: **the ISIs are not independent**.

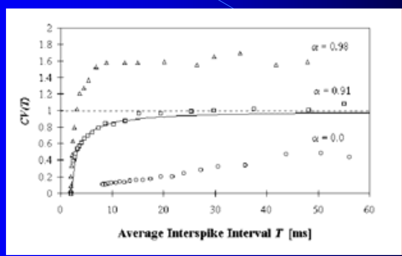
Christodoulou, C. & Bugmann, G. (2001). ***Neurocomputing*****, 38-40**, 1141-1149.

Effect of concurrent excitation and inhibition on firing variability

Main Conclusions:

- **Approximately 80% inhibition on concurrent excitation produces *near* Poissonian-type firing at high firing rates.**
- **The presence of clusters at short intervals increases the C_V values.**
- **The ISIs are not independent indicating that the firing is not completely Poissonian. Thus, this mechanism is not likely to reflect the firing mechanism in cortical cells.**

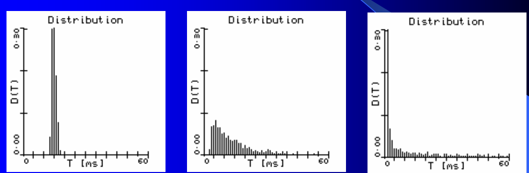
Firing variability at different levels of somatic reset (Leaky Integrate-and-Fire model)



With partial somatic reset then after each firing at time t: $V(t + \Delta t) \rightarrow \alpha V(t)$; where α is the reset parameter $\in [0,1]$

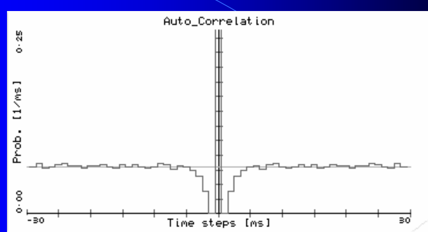
Bugmann, G., **Christodoulou C.** & Taylor, J. G. (1997). ***Neural Computation*****, 9**, 985-1000.

ISI histogram distributions for different levels of somatic reset (Δt_M = 15ms)



α = 0, total reset   α = 0.91, closest to Poisson   α = 0.98, bursting

Autocorrelogram for the Leaky Integrate-and-Fire neuron with partial somatic reset at 91% of the threshold value



Δt_M = 15.4ms; t_R = 2ms; C_V = 0.85; time step = 1ms

- Apart from a small depletion in intervals close to the refractory time, the curve is flat, indicating **independence of the ISIs**.

Christodoulou, C. & Bugmann, G. (2001). ***Neurocomputing*****, 38-40**, 1141-1149.

Effect of partial somatic reset on firing variability

Main Conclusions:

- **Highly irregular firing can be produced with a Leaky Integrate-and-Fire model equipped with a partial somatic reset mechanism.**
- **The irregular firing is of Poisson type**
  - **verified by examination of the ISIs, which showed that they are both: (a) exponentially distributed and (b) independent**

Thus:
Partial somatic reset mechanism is a strong candidate for the one used in the brain for producing irregular firing

Bugmann, G., **Christodoulou C.** & Taylor, J. G. (1997). ***Neural Computation***, **9**, 985-1000.
Christodoulou, C. & Bugmann, G. (2001). ***Neurocomputing***, **38-40**, 1141-1149.

Effect on firing variability of partial somatic reset – Other Conclusions:

- High variable firing was a result of both temporal integration of random EPSPs and current fluctuation detection; reverse correlation graphs cannot reliably quantify the contribution of each of these mechanism to the firing irregularity.
- Partial somatic reset is also a powerful parameter to control the gain of the neuron.

Bugmann, G., Christodoulou C. & Taylor, J. G. (1997). ***Neural Computation***, **9**, 985-1000.

Neural Code – open questions & current ongoing work:

Ascertain:

1. *Whether a firing pattern does indeed represent a `code`*, i.e., What actually constitutes a code?

**** Test whether a code has the information to perfom a particular task (mostly experimental)**

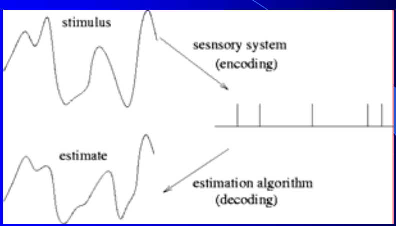
Neural Code – open questions & current ongoing work:

Ascertain:

2. *What type of code does a firing pattern represent?*

- **** Development of analytical reverse correlation techniques to quantify the relative contribution of the input current fluctuations & temporal integration to the high firing variability**
- **** Information theory.**
- **** Relate the input current and each output spike: "What can an organism learn *for* a sensory input given an output spike train?" (Bialek et al. , 1991).**

Stimulus Reconstruction



Bialek et al, 1991

Further reading

- Spiking Neuron Models: Single Neurons, Populations and Plasticity, W. Gerstner and W. M Kistler, Cambridge University Press, 2002, Chapter 1, Section 1.4-1.7: diwww.epfl.ch/~gerstner/BUCH.html
- Spikes: Exploring the Neural Code. F. Rieke, D. Warland, R. de Ruyter van Stevenick and W. Bialek, MIT Press, 1999.
- Theoretical Neuroscience: Computational and Mathematical Modelling of Neural Systems, P. Dayan and L. Abbott, MIT Press, 2001, Ch 1.
- Gabbiani, F. and Koch, C. "Principles of Spike Train Analysis" in Koch, C. and Segev, I., editors (1998). *Methods in Neuronal Modelling: From Ions to Networks*. MIT Press, Cambridge, Massachusetts, 2nd edition (www.klab.caltech.edu/MNM/gabbiani-koch-98.pdf)
- Parker & Newsome (1998), Sense and the single neuron: probing the physiology of perception. *Annual Review of Neuroscience*, **21**, 227-277 (monkeybiz.stanford.edu/pdf/parker_1998.pdf) (*supports rate code*)
- Christodoulou, C. and Bugmann, G. (2000). Near-Poisson-Type Firing Produced by Concurrent Excitation and Inhibition. ***Biosystems*** , **58**, 41-48.

Further Reading

- Softky, W. R. & Koch, C. (1993). The Highly Irregular Firing of Cortical Cells Is Inconsistent with Temporal Integration of Random EPSP's. *J. of Neurosci.*, **13** (1), 334-530.
- Shadlen, M. N. & Newsome, W. T. (1994). Noise, neural codes and cortical organisation *Curr. Opin. Neurobiol.*, **4**, 569-579.
- Shadlen, M. N. & Newsome, W. T. (1998). The variable discharge of cortical neurons: Implications for connectivity, computation, and information coding. *J of Neurosci.*, **18**, 3870-3896.
- Feng, J. & Brown, D. (1998). Impact of temporal variation and the balance between excitation and inhibition on the output of the perfect integrate-and-fire model. *Biol. Cybern.*, **78**, 369-376.
- Feng, J. & Brown, D. (1999). Coefficient of Variation of interspike intervals greater than 0.5. How and when? *Biol. Cybern.*, **80**, 291-297.
- Stevens, C. F. & Zador, A. M. (1998). Input synchrony and the irregular firing of cortical neurons. *Nature Neurosci.* **1**, 210-217.
- **Christodoulou, C.** and Bugmann, G. (2001). Coefficient of Variation (CV) vs Mean Interspike Interval (ISI) curves: what do they tell us about the brain? ***Neurocomputing***, **38-40**, 1141-1149.
- **Christodoulou, C.**, Bugmann, G. and Clarkson, T. G. (2002). A Spiking Neuron Model: Applications and Learning. ***Neural Networks***, **15**, 891-908.
- Bugmann, G., **Christodoulou, C.** and Taylor, J. G. (1997). Role of the Temporal Integration and Fluctuation Detection in the Highly Irregular Firing of a Leaky Integrator Neuron with Partial Reset. ***Neural Computation*** , **9**, 5, 985-1000.

Further Reading

- Lin, J.K., Pawelzik, K., Ernst, U., Sejnowski, T., 1998. Irregular synchronous activity in stochastically-coupled networks of integrate-and-fire neurons. *Netw.: Comput. Neural Syst.* 9, 333–344.
- Usher, M., Stemmler, M., Koch, C., & Olami, Z. (1994). Network amplification of local fluctuations causes high spike rate variability, fractal firing patternsand oscillatory local-field potentials. *Neural Computation*, *6*, 795–836.
- Shadlen MN, Newsome WT (1995) Is there a signal in the noise? *Curr Opin Neurobiol* 5:248-250 (supports the rate code – integration)
- Softky WR (1995) Simple codes versus efficient codes, *Curr Opin Neurobiol* 5:239-47 (supports the temporal code – coincidence detection)
- Agmon-Snir H, Segev I (1993) Signal delay and input synchronization in passive dendritic structures, *J Neurophysiol*, 70:2066-2085 (supports rate and temporal coding are both segregated in the dendritic tree)
- Neural Codes and Distributed Representations: Foundations of Neural Computation. L. Abbott and T. Sejnowski (eds.), MIT Press, 1999.