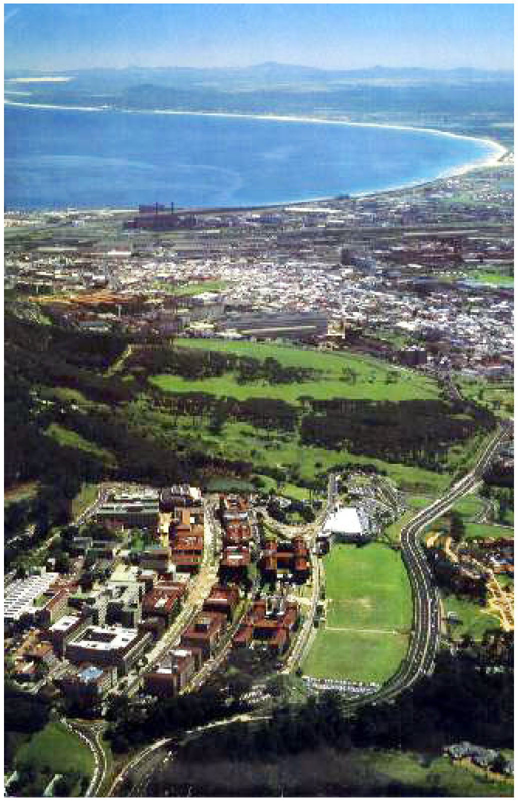
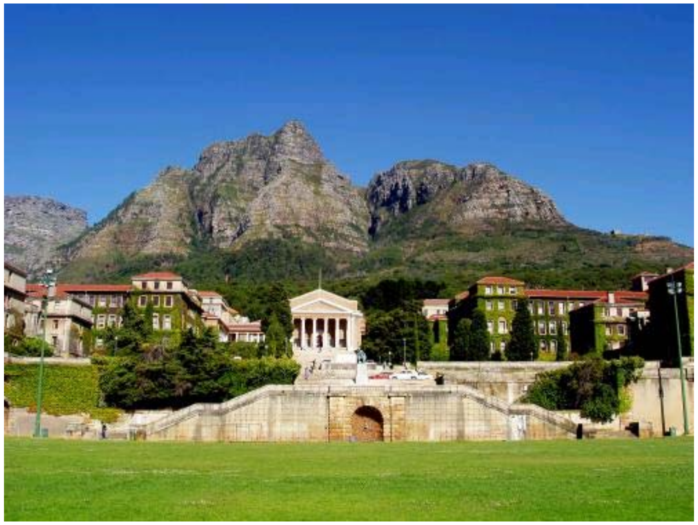
# Three Topics in Neural Dynamics:

# Correlation, Supercritical Stability, & Event-Based Control






Jonathan Tapson

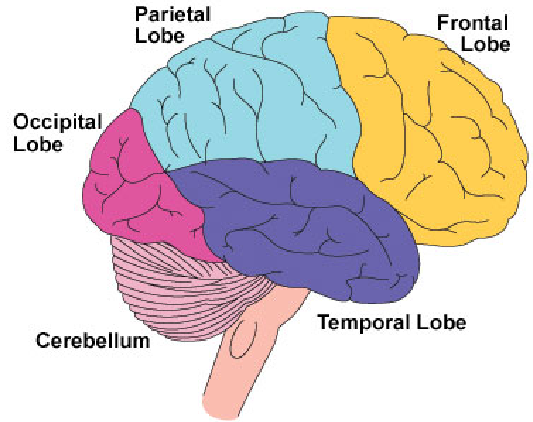
University of Cape Town


Neuromorphic Engineering Workshop

Telluride, 2007

# Why these topics?

- Implementation and detection of correlations
  - Role of stochastic processes in neural systems
    - Connects neuromorphic engineering to statistical signal processing
    - Neuromorphic → mainstream application: GPS system
- Supercritical stability: feedback in sensory systems
  - Role of local feedback in neural systems
    - Connects neuromorphic engineering to nonlinear theory
    - Neuromorphic → mainstream application: Sonar
- Event-based control systems
  - Closing the control loop in sensor-actuator systems
    - Connects neuromorphic engineering to classic control and network theory




Mandatory picture of the brain

# Implementation and Detection of Correlations

- What do we mean by correlation in the neuromorphic context?
  - We compare one signal with another to get two measures:
    - How similar are they?
    - How are they placed relative to one another in time and/or space?

- What kind of signals?
  - Sounds (auditory system)
  - Scenes (vision system)
  - Patterns of neural excitation (associative or content-addressable memory)

# Key

- Mainstream theory:

- Recent result, not necessarily peer reviewed:

- Reckless conjecture:

# The roles of correlation in sensory systems

- Auditory system
  - Detection of interaural time differences for:
    - Sound localization
    - Source separation
  - Autocorrelation (detection of periodicities in a signal)
    - Pitch perception
    - Timbre processing

- Vision system
  - Detection of movement
    - Self motion
    - Tracking of moving objects

# Mathematical Correlation

- Autocorrelation function of a signal f(t):

$$R_{ff}(\tau) = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} f(t) f(t+\tau) dt$$

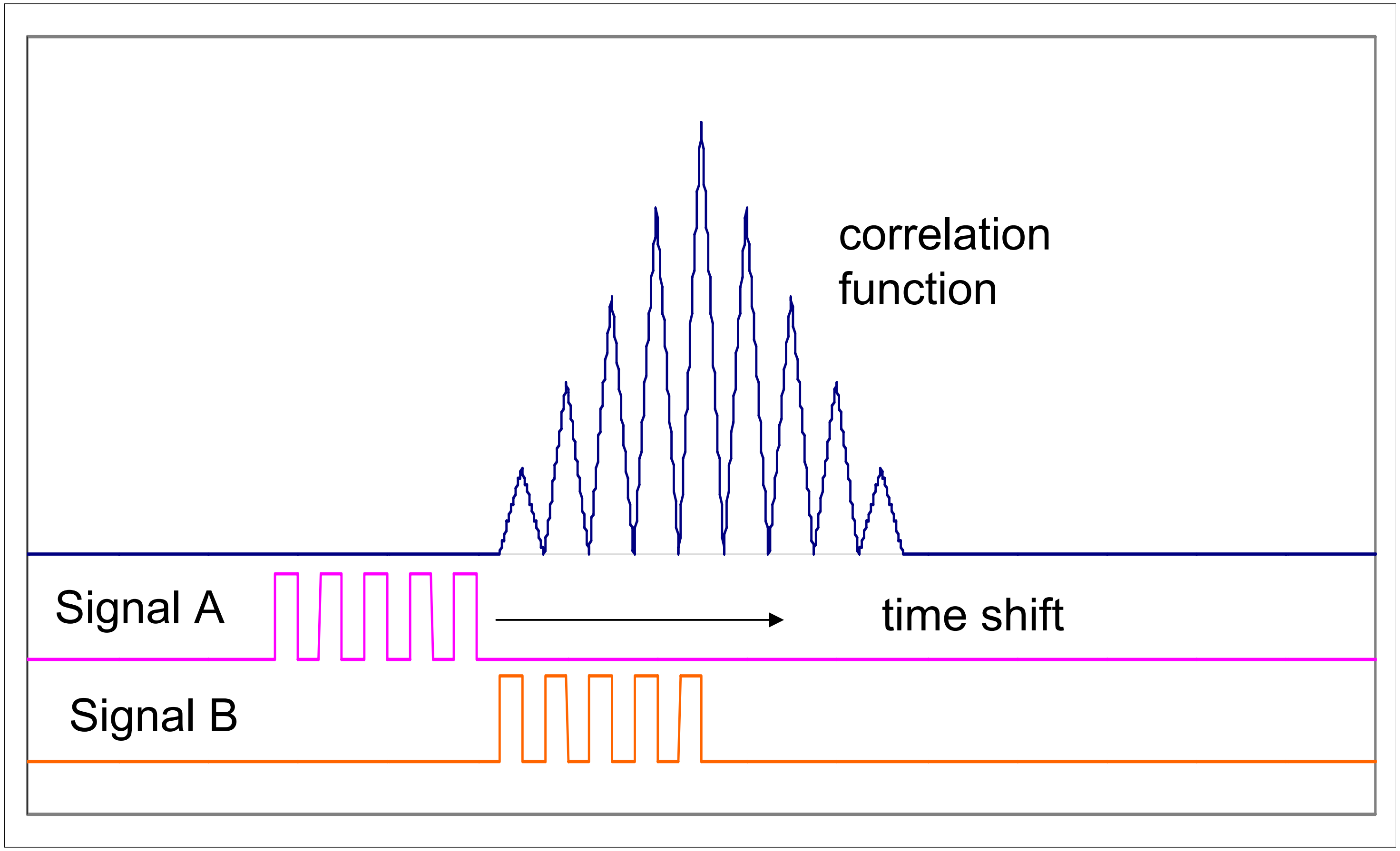
- Cross-Correlation
  - Periodic

$$R_{fg}(\tau) = \frac{1}{T} \int_{0}^{T} f(t) g(t+\tau) dt$$

  - Non-periodic

$$R_{fg}(\tau) = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} f(t) g(t+\tau) dt$$

# Auto- and cross-correlation



## The physiological origin of neural correlation

- In order to correlate we need to:
  - Multiply two signals together
  - Time shift one signal relative to the other
  - Integrate

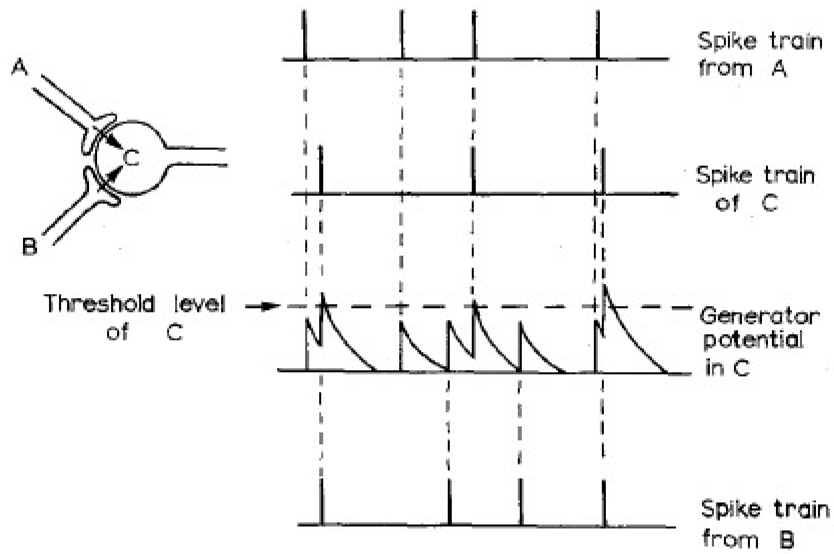
$$R_{fg}(\tau) = \frac{1}{T}\int_0^T f(t)g(t+\tau)dt$$

# The physiological origin of neural correlation

Biol. Cybernetics 21, 227—236 (1976)


## A Proposed Mechanism for Multiplication of Neural Signals

Mandyam V. Srinivasan and Gary D. Bernard

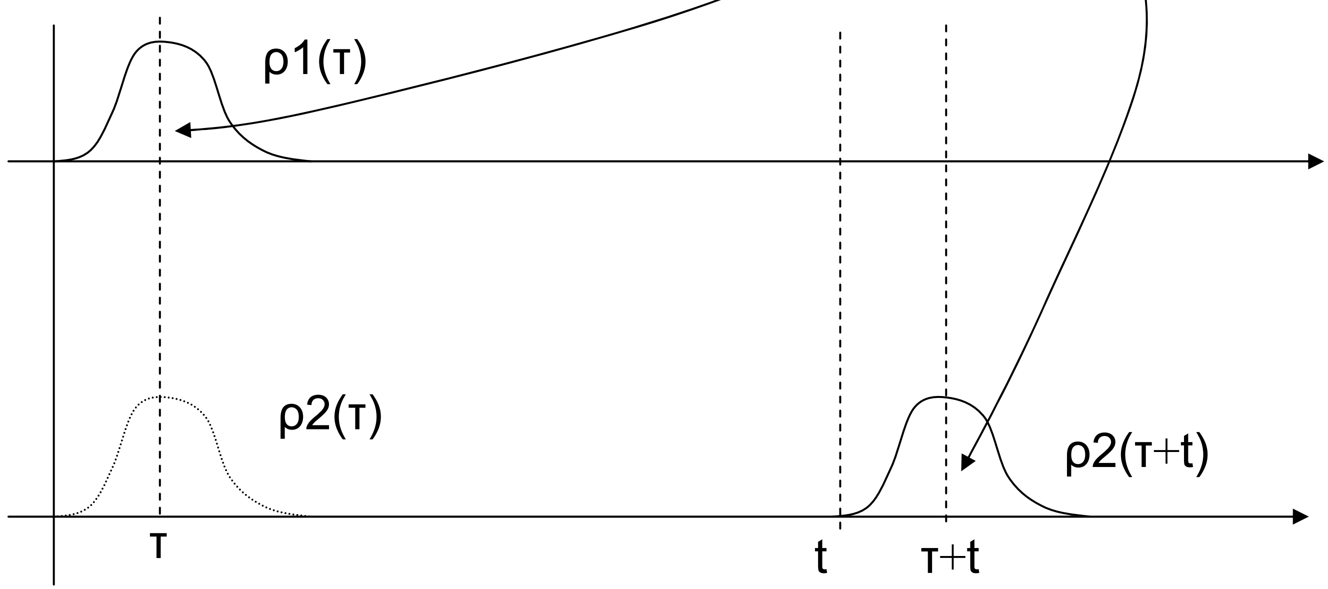


# Multiplication

If we have two independent events A and B with probabilities ρ(A) and ρ(B) then the probability of both A and B occurring is:

ρ(A and B) = ρ(A)ρ(B)

Probability of two spikes here and here is ρ1(τ)ρ2(τ+t)



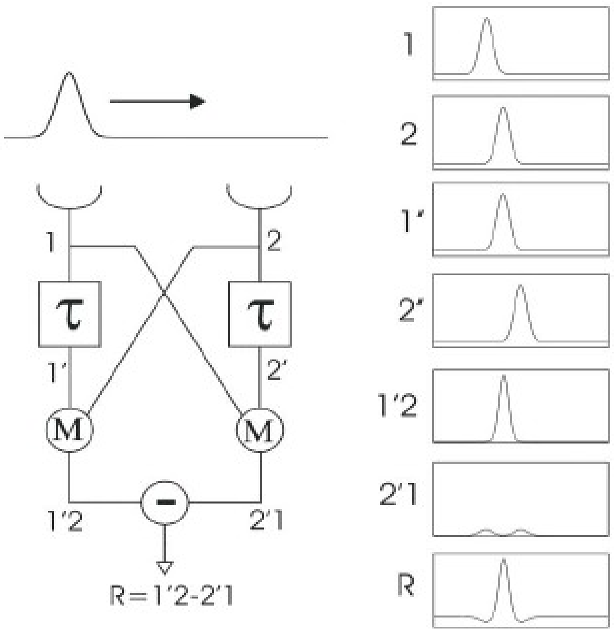
# Coincidence Detectors



Chapter 14:

By A. Borst

Ed: Jianfang Feng




First described by Reichart in ?1959?

**Figure 14.2**

**Minimal circuit diagram of a correlation detector. It consists of two subunits. In each subunit, the retinal signals from two neighboring locations are multiplied with each other (M), after one or both of them have been fed through a temporal filter with a time constant $\tau$. This operation is done twice in a mirror-symmetrical way in both subunits. The output signals of both subunits are finally subtracted.**

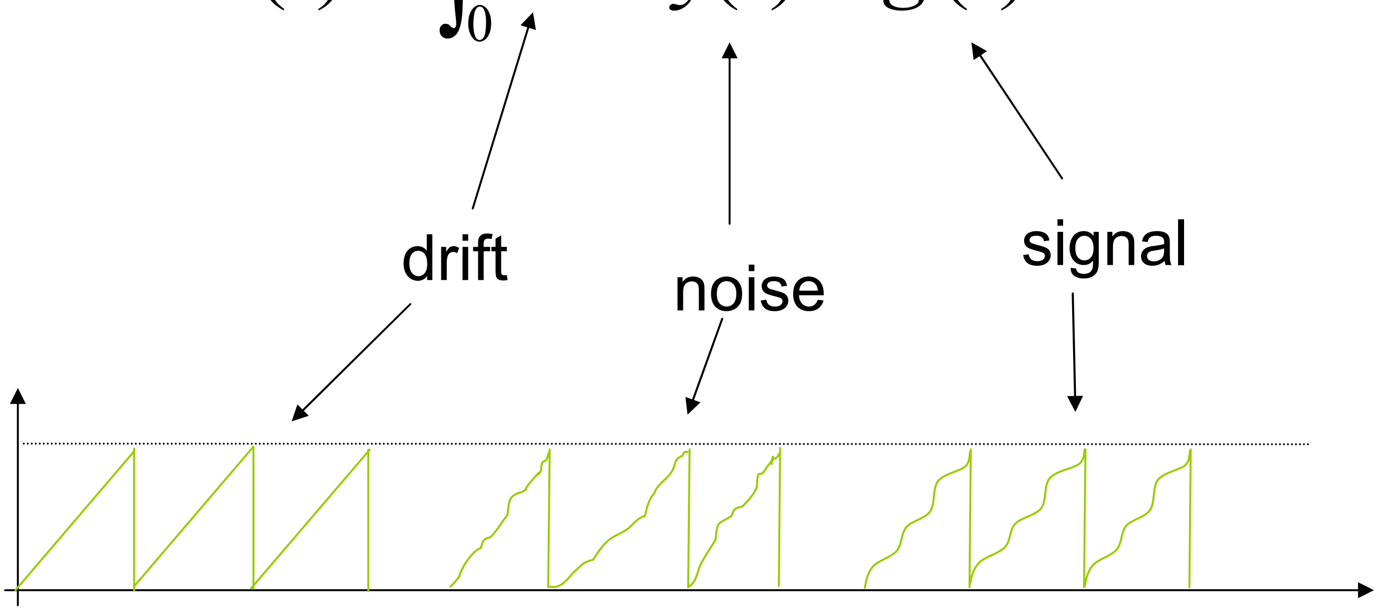
## Development of a wide-range correlation detector

- Integrate-and-fire processes
- Stochastic autocorrelation
- Neural simulation
- Autocorrelation in the auditory nerve
- A cross-correlation circuit

# Integrate-and-fire process

- Integrate-and-fire membrane potential:

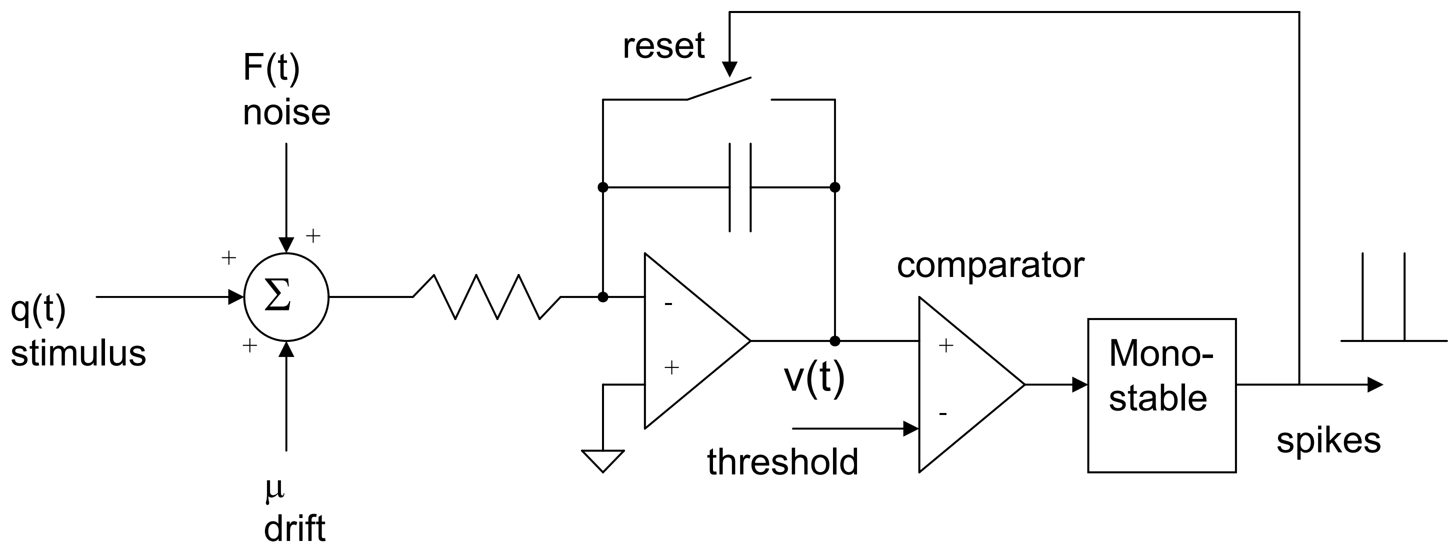
$$v(t) = \int_0^t m + \xi(t) + g(t)dt$$




Reset to V = 0 after firing at threshold  V = θ

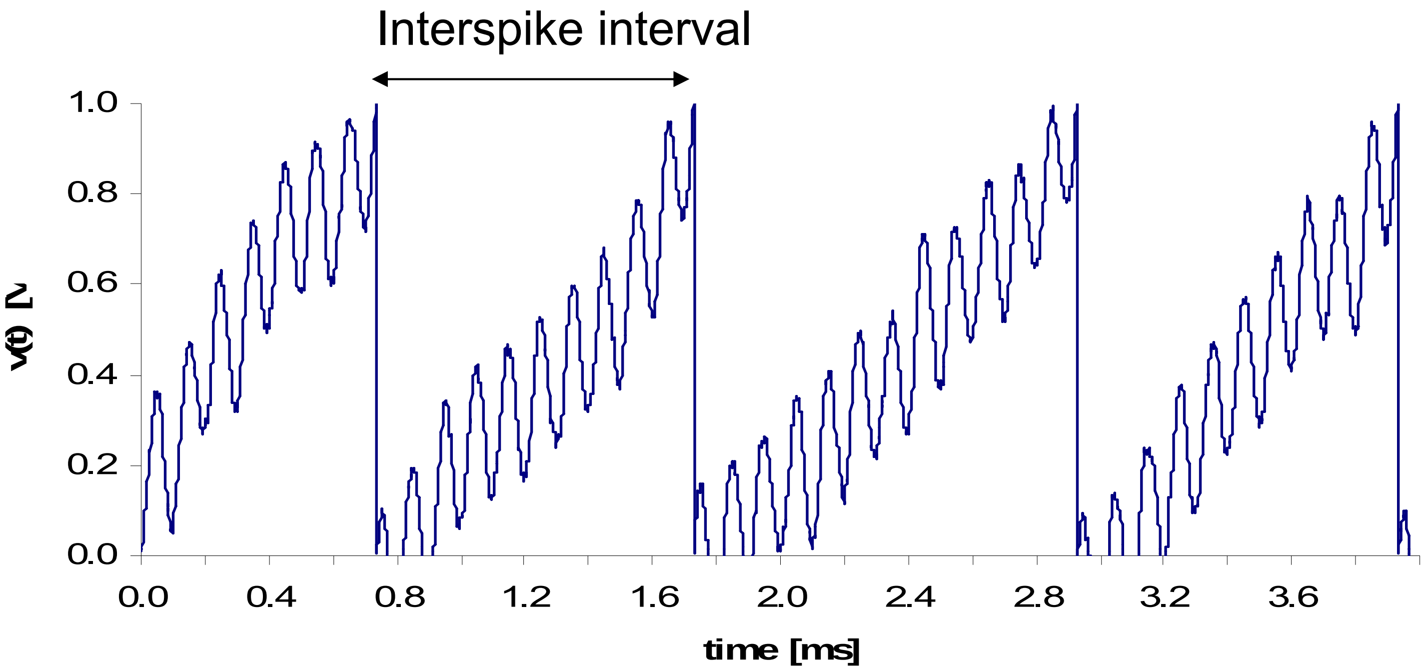
# Integrate-and-fire process

- Integrate-and-fire circuit (relaxation oscillator):



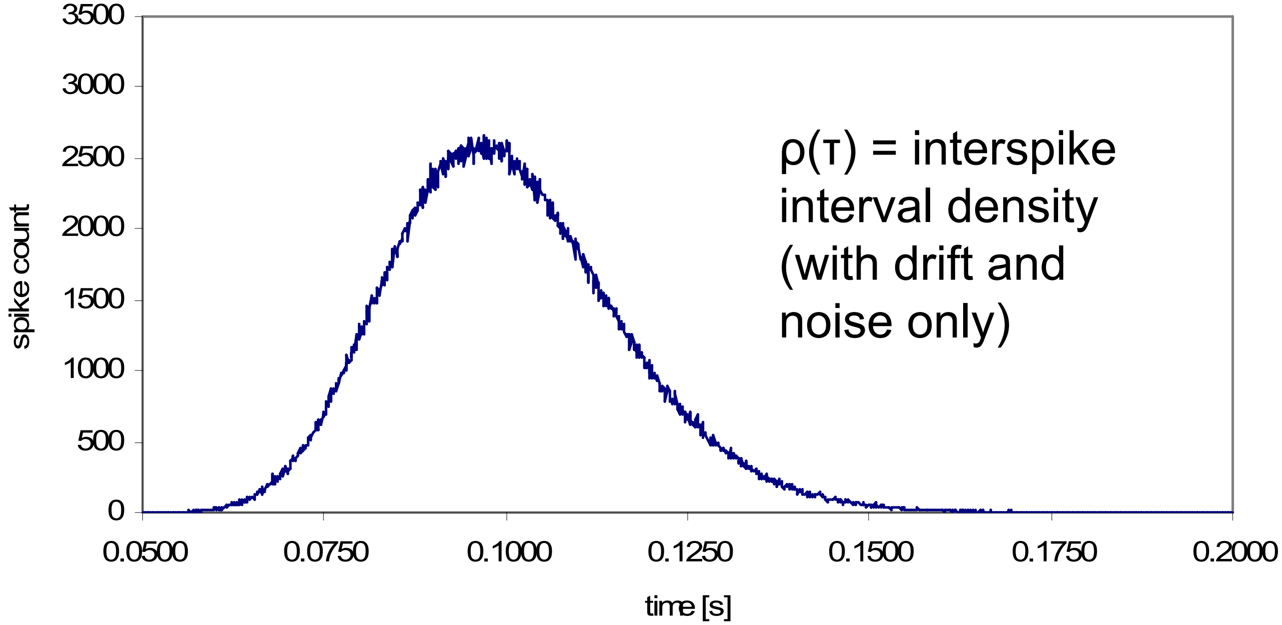
# Integrate-and-fire process

- Typical v(t) waveform (sinusoidal input):



# Stochastic autocorrelation

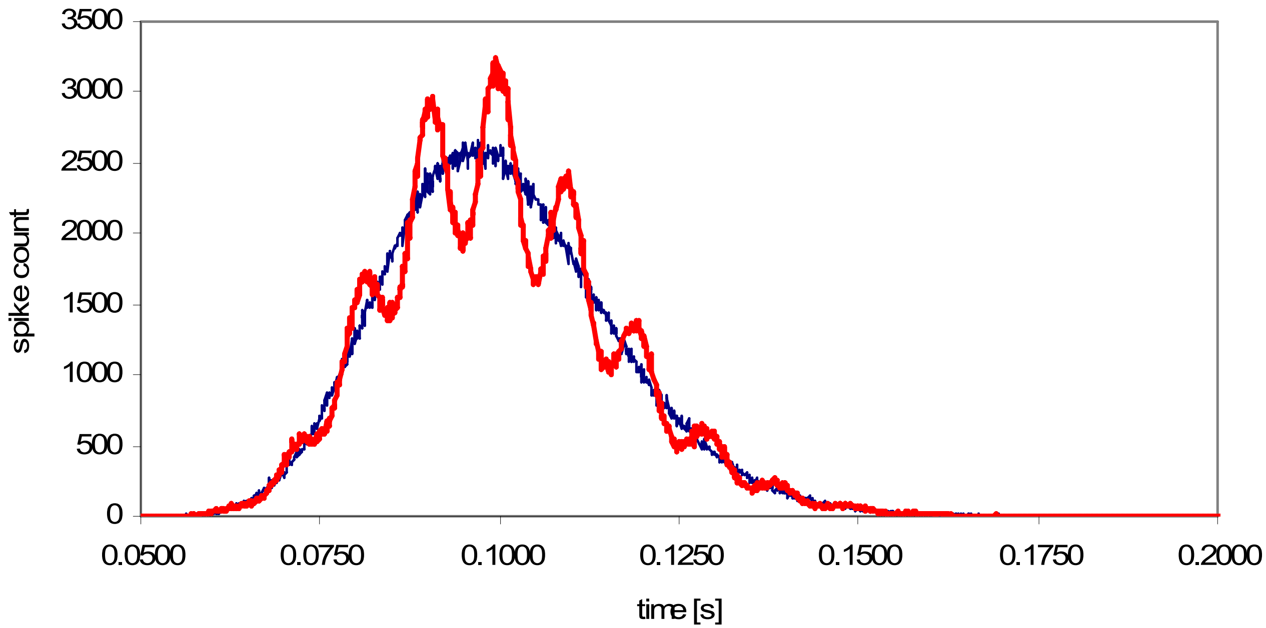
- The interspike interval histogram (ISIH):



# Stochastic autocorrelation

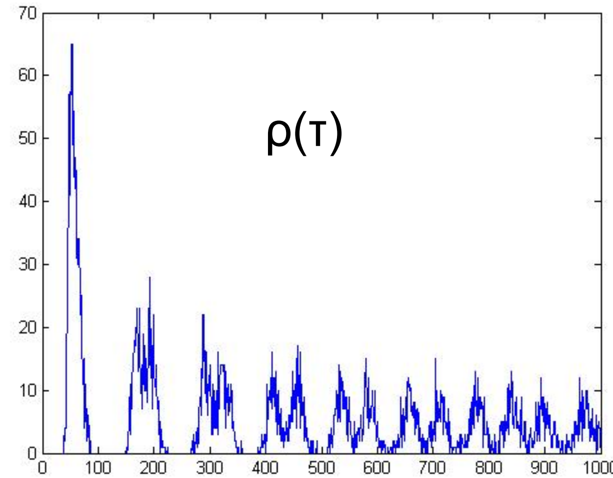
- The interspike interval histogram (ISIH):

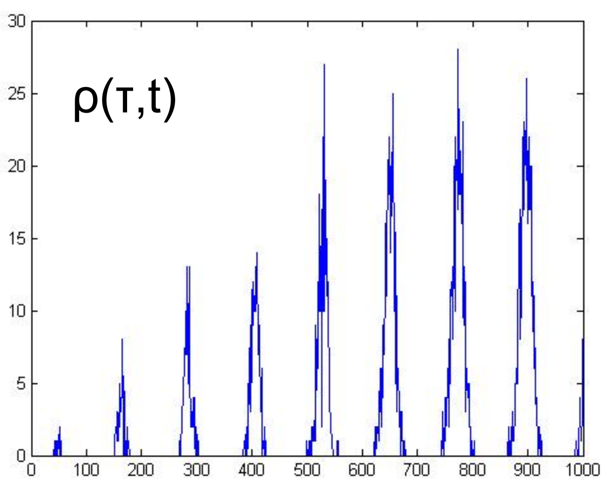
With sine input: $g(t) = A\sin(\omega t + \varphi)$

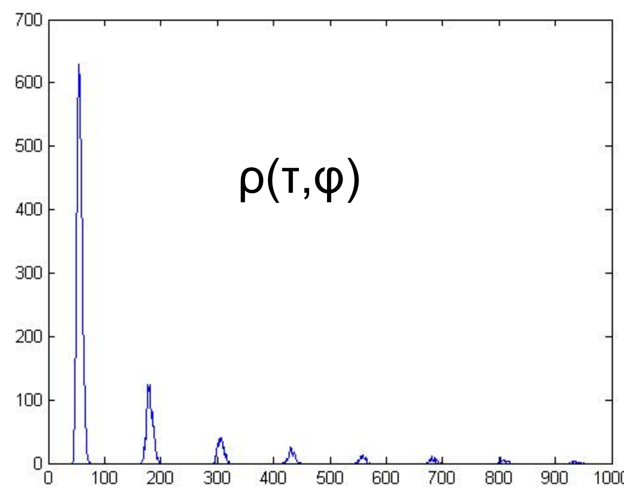


# What do we do with the starting phase of g(t)?

- Sine wave input with identical parameters, except…
  - Random phase start
  - Same phase start
  - Continuous (started where
  - last trial ended)

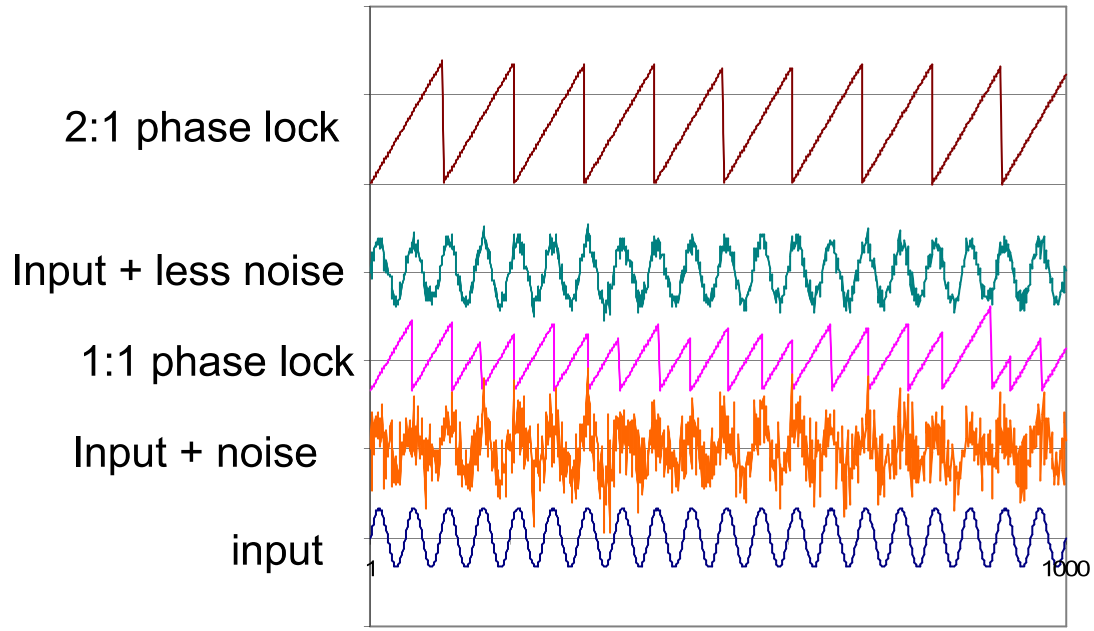


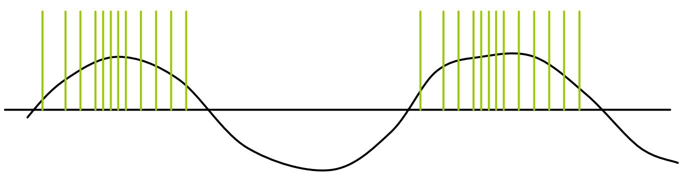



# Neurons operate in different regimes

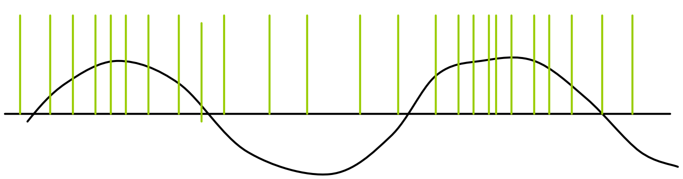
- Phase locking
  - Simple 1:1
  - Complex m:n




- Refractory spiking

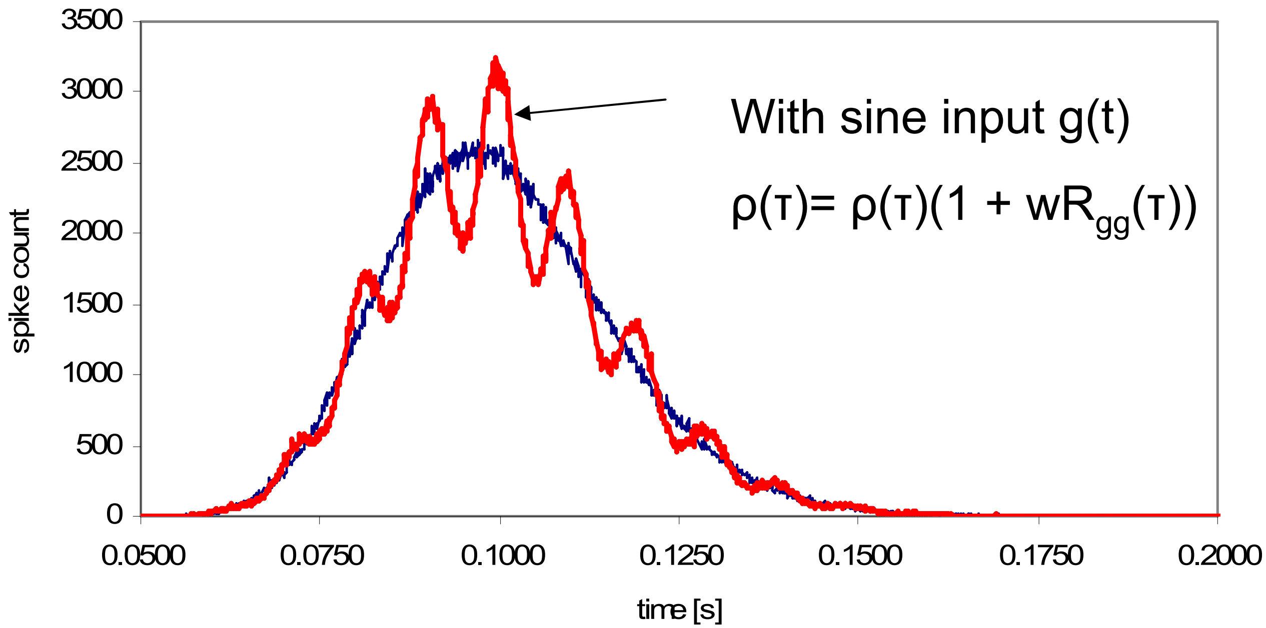


- Unsynchronized



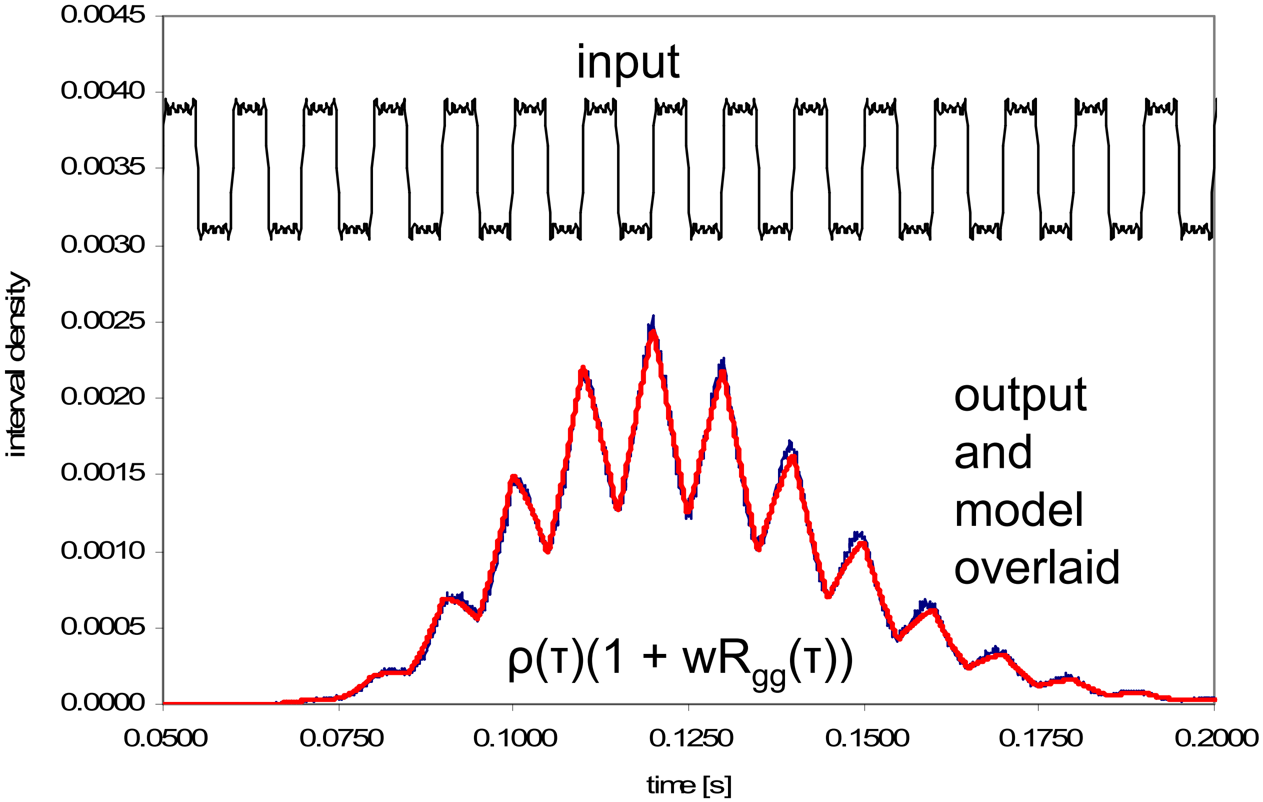
# Stochastic autocorrelation

- The interspike interval histogram (ISIH):



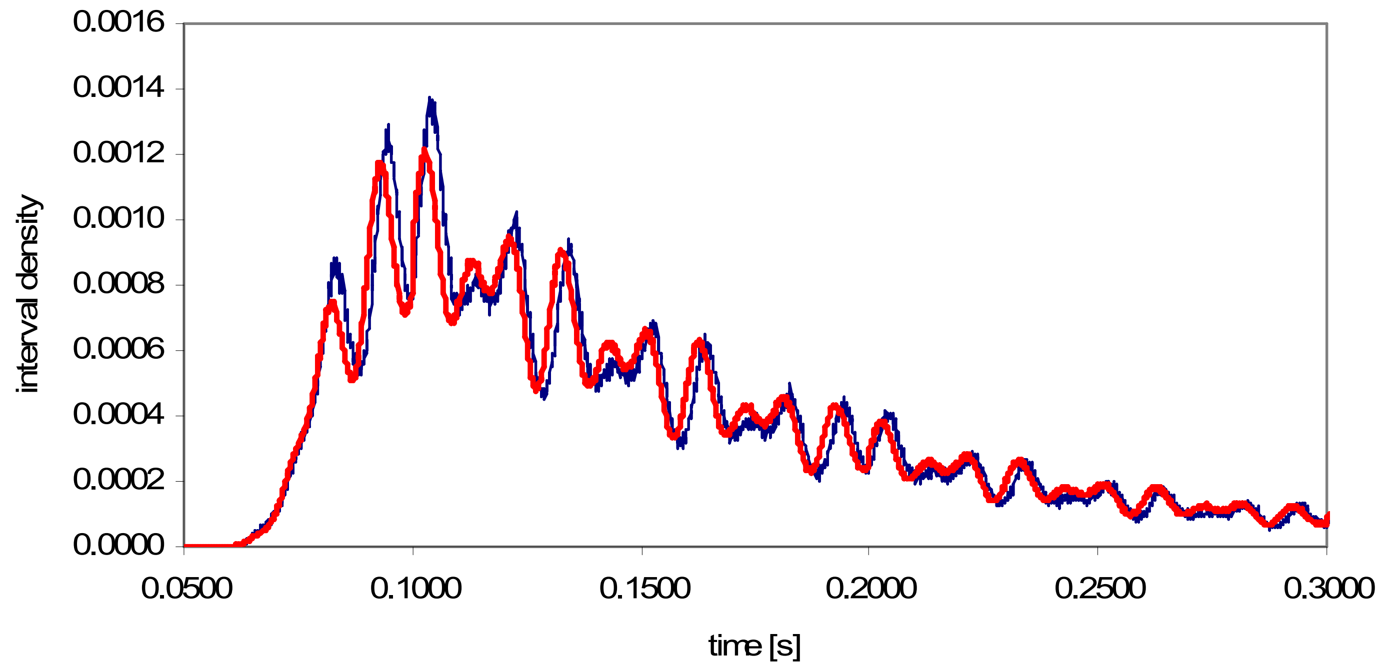
# Stochastic autocorrelation

- Autocorrelation output:



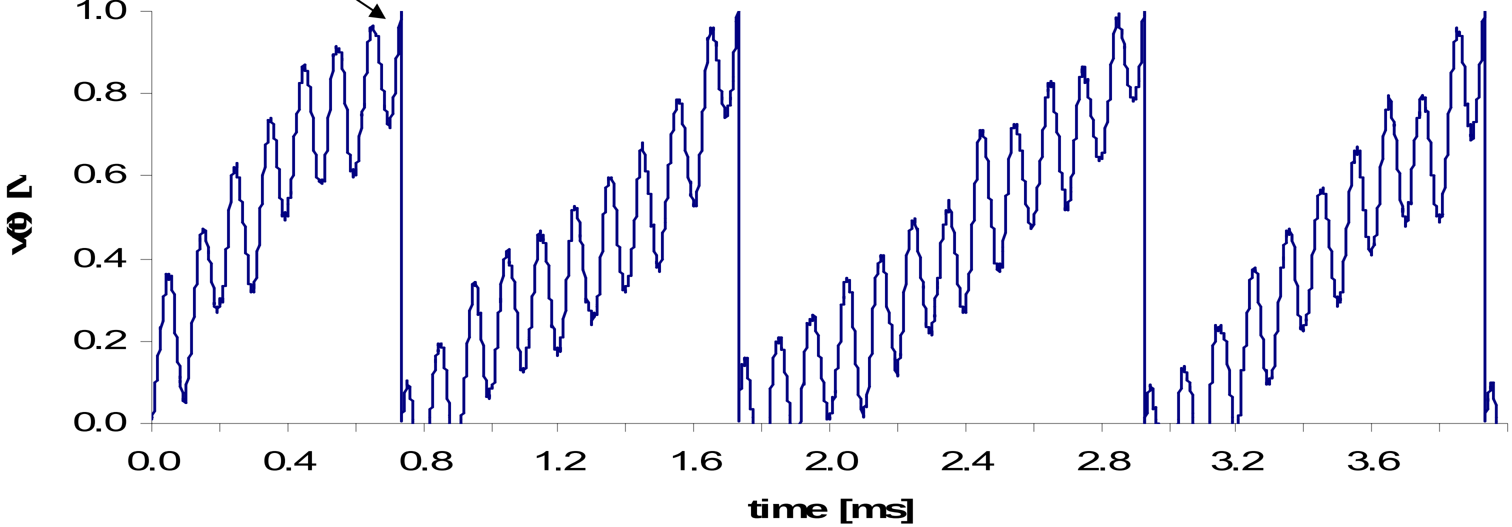
# Further examples of stochastic autocorrelation (>9000 available)

- Random periodic signal, neuron with refractory period and quadratic leakage

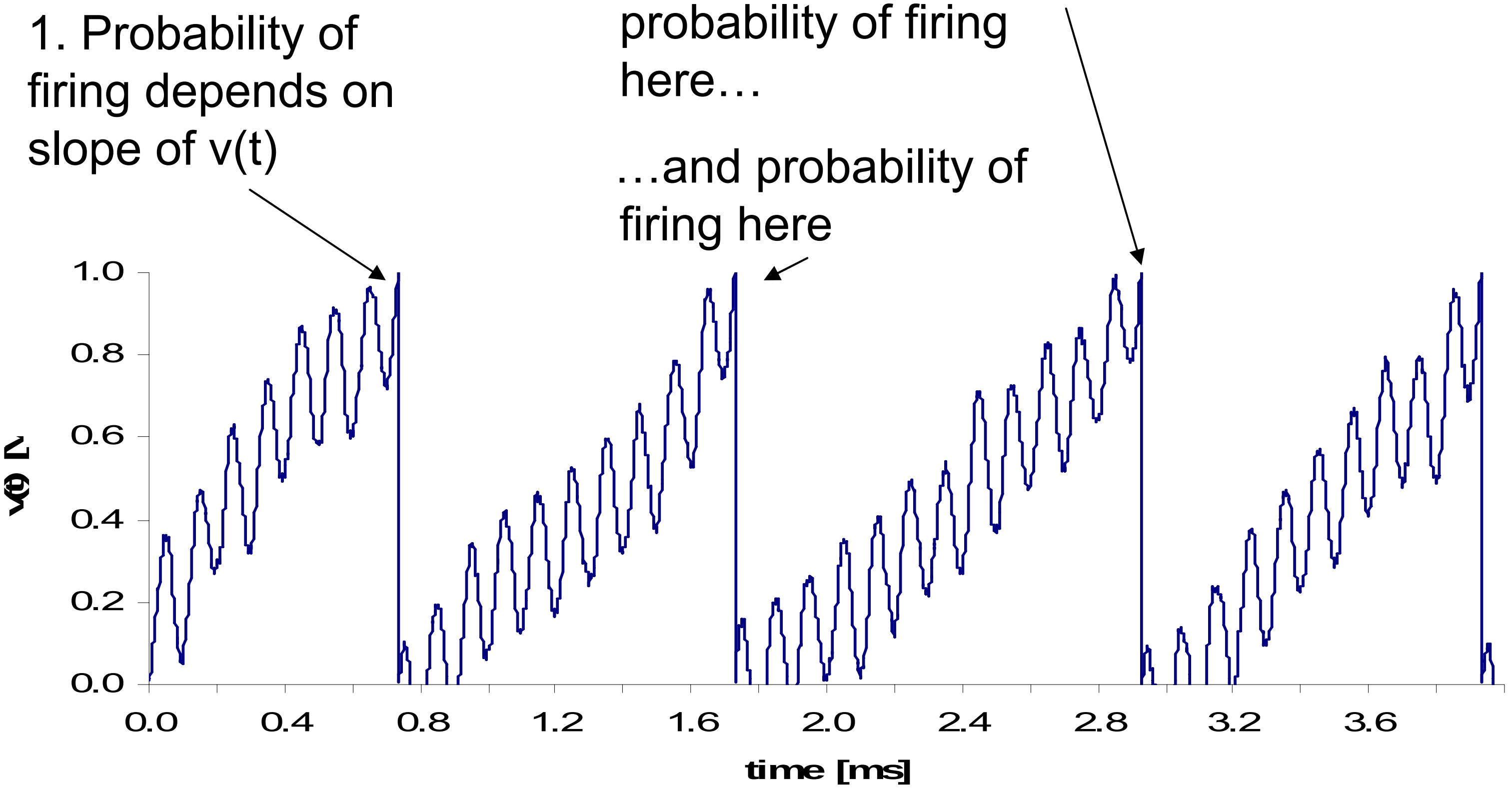


# What affects the ISIH?

1. Probability of firing depends on slope of v(t)



# What affects the ISIH?



# Stochastic autocorrelation

- Modulation of slope of v(t) at threshold:

$$\frac{dv(t)}{dt} = \frac{d}{dt}\int_{t_0}^{t_0+\tau} m + \varsigma(t) + g(t)dt$$

$$\left.\frac{dv(t)}{dt}\right|_{v\to\theta} = m + \varsigma(t) + g(t)$$

# Stochastic autocorrelation

- Markov nature of firing times:

$$\rho_{LP}(\tau | t_0) = \rho(\tau)(1 + wg(t_0 + \tau))$$

$Y_n(\mathbf{t})$ = Prob of sequence $\mathbf{t} = [t1, t2, \ldots tn]$

$$Y_n(\mathbf{t}) = \rho_{LP}(t_n | t_{n-1}) \times \rho_{LP}(t_{n-1} | t_{n-2}) \times \rho_{LP}(t_{n-2} | t_{n-3}) \ldots$$

$$= \prod_{k=1}^{n} \rho_{LP}(t_k - t_{k-1} | t_{k-1})$$

$$= \prod_{k=1}^{n} \rho(t_k - t_{k-1})(1 + wg(t_k))$$

# Stochastic autocorrelation

- Marginalize to eliminate primary Markov property:

$$q_{t_2-t_1}(\tau) = \{\text{Prob that first and second spikes after } t_0 \text{ are separated by } \tau\}$$

$$= \int_{t_0}^{\infty} \prod_{k=1}^{2} \rho_{LP}\left(t_k - t_{k-1} \middle| t_{k-1}\right) dt_1 \text{ for } \mathbf{t} = [t_1, t_1 + \tau]$$

$$= \int_{t_0}^{\infty} \rho_{LP}\left(t_1 + \tau \middle| t_1\right) \rho_{LP}\left(t_1 \middle| t_0\right) dt_1$$

$$= \int_{t_0}^{\infty} \rho(\tau) \rho(t_1 - t_0)(1 + wg(t_1 + \tau))(1 + wg(t_1)) dt_1$$

$$= \int_{t_0}^{\infty} \rho(\tau)\rho(t_1 - t_0) dt_1 + w\int_{t_0}^{\infty} \rho(\tau)\rho(t_1 - t_0) g(t_1 + \tau) dt_1$$

$$+ w\int_{t_0}^{\infty} \rho(\tau)\rho(t_1 - t_0) g(t_1) dt_1 + w^2 \int_{t_0}^{\infty} \rho(\tau)\rho(t_1 - t_0) g(t_1 + \tau) g(t_1) dt_1$$

$$q_{t_2-t_1}(\tau) = \rho(\tau) + w^2 \rho(\tau) \int_{t_0}^{\infty} g(t_1 + \tau) g(t_1) dt_1$$

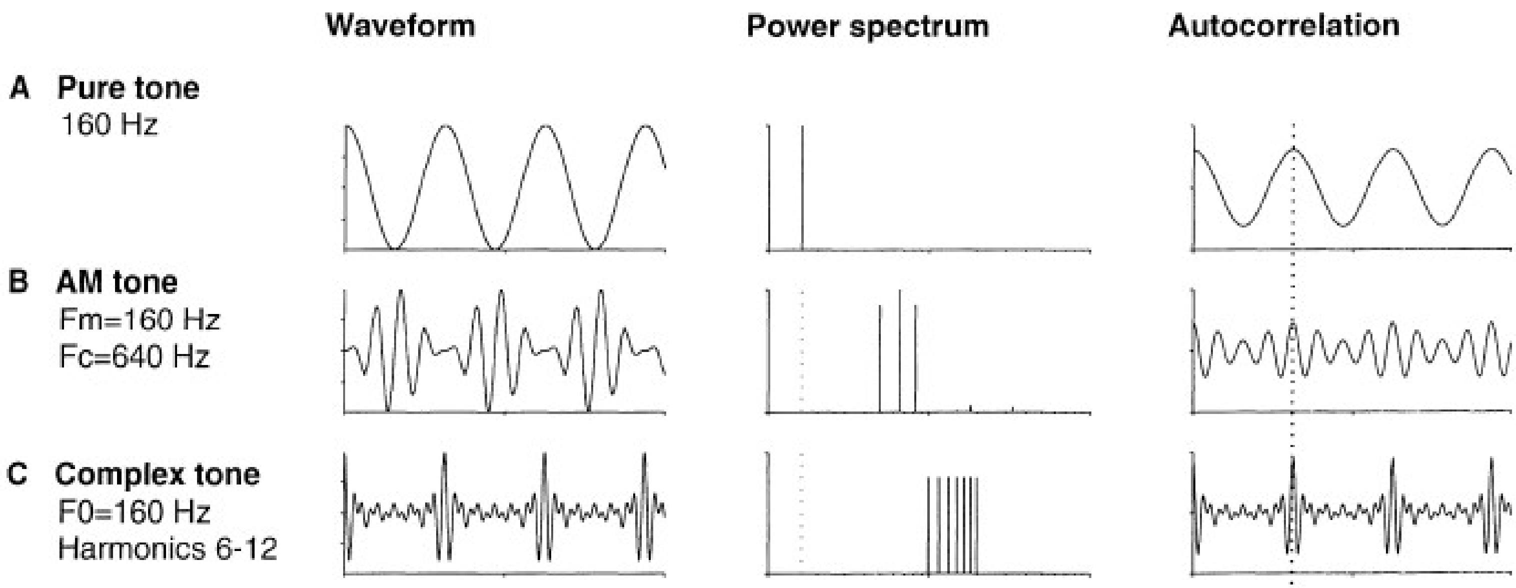
$$= \rho(\tau)\left(1 + w^2 R_{gg}(\tau)\right)$$

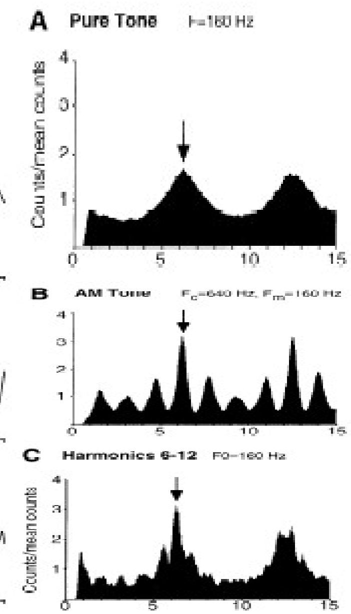
# Autocorrelation in the auditory nerve

Journal of Neurophysiology
Vol. 76, No. 3, September 1996. *Printed in U.S.A.*

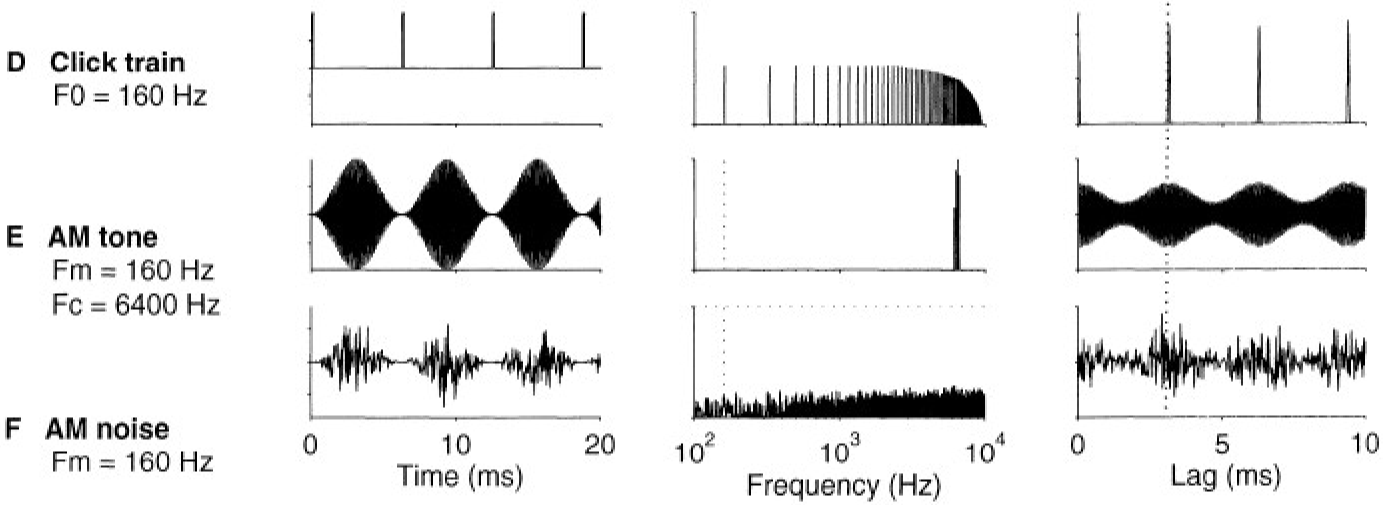
## Neural Correlates of the Pitch of Complex Tones. I. Pitch and Pitch Salience

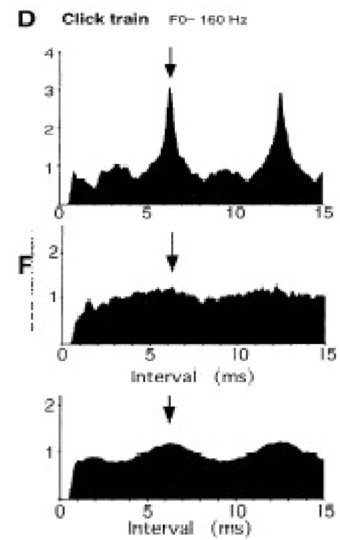
PETER A. CARIANI AND BERTRAND DELGUTTE



# Autocorrelation in the auditory nerve

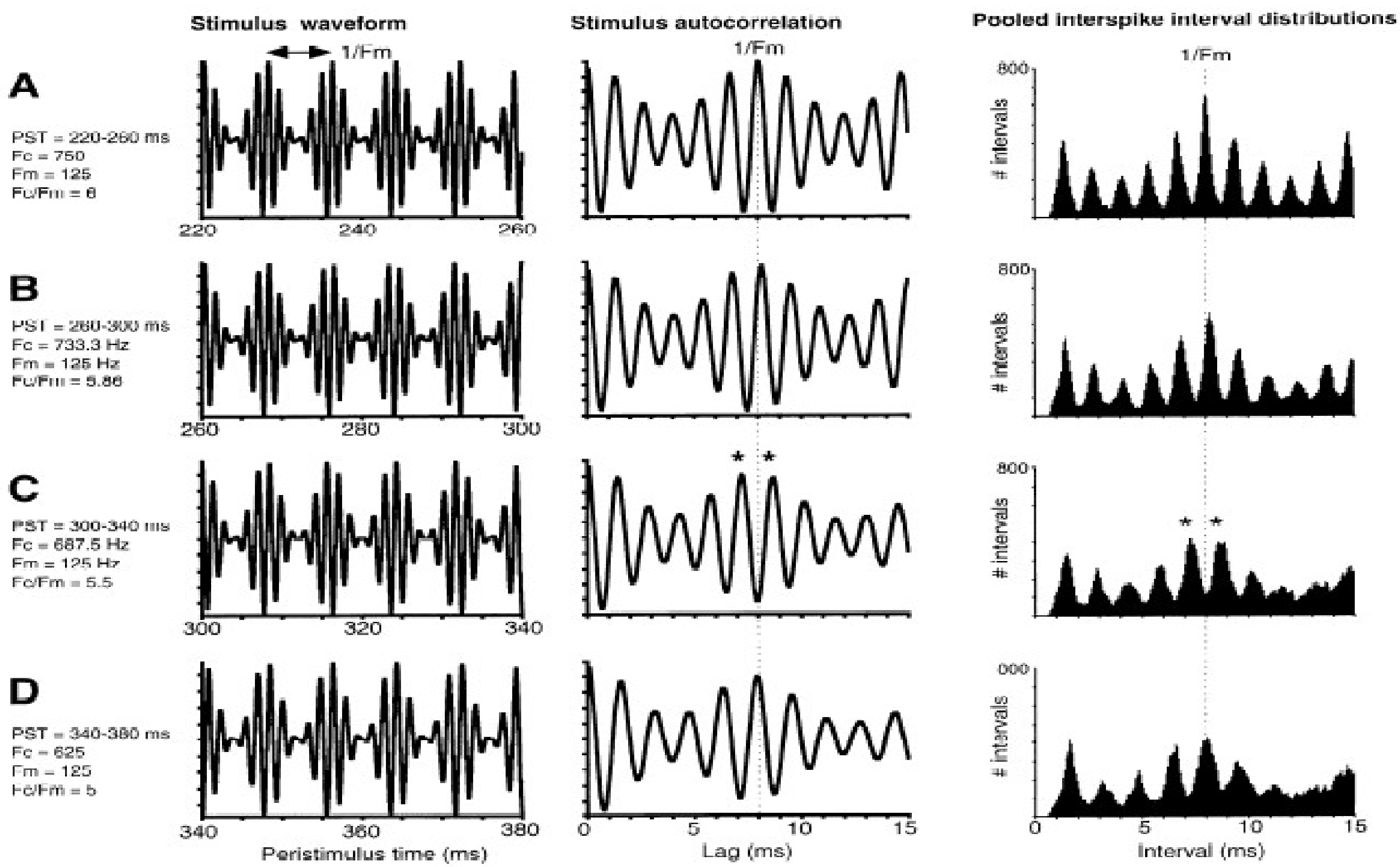


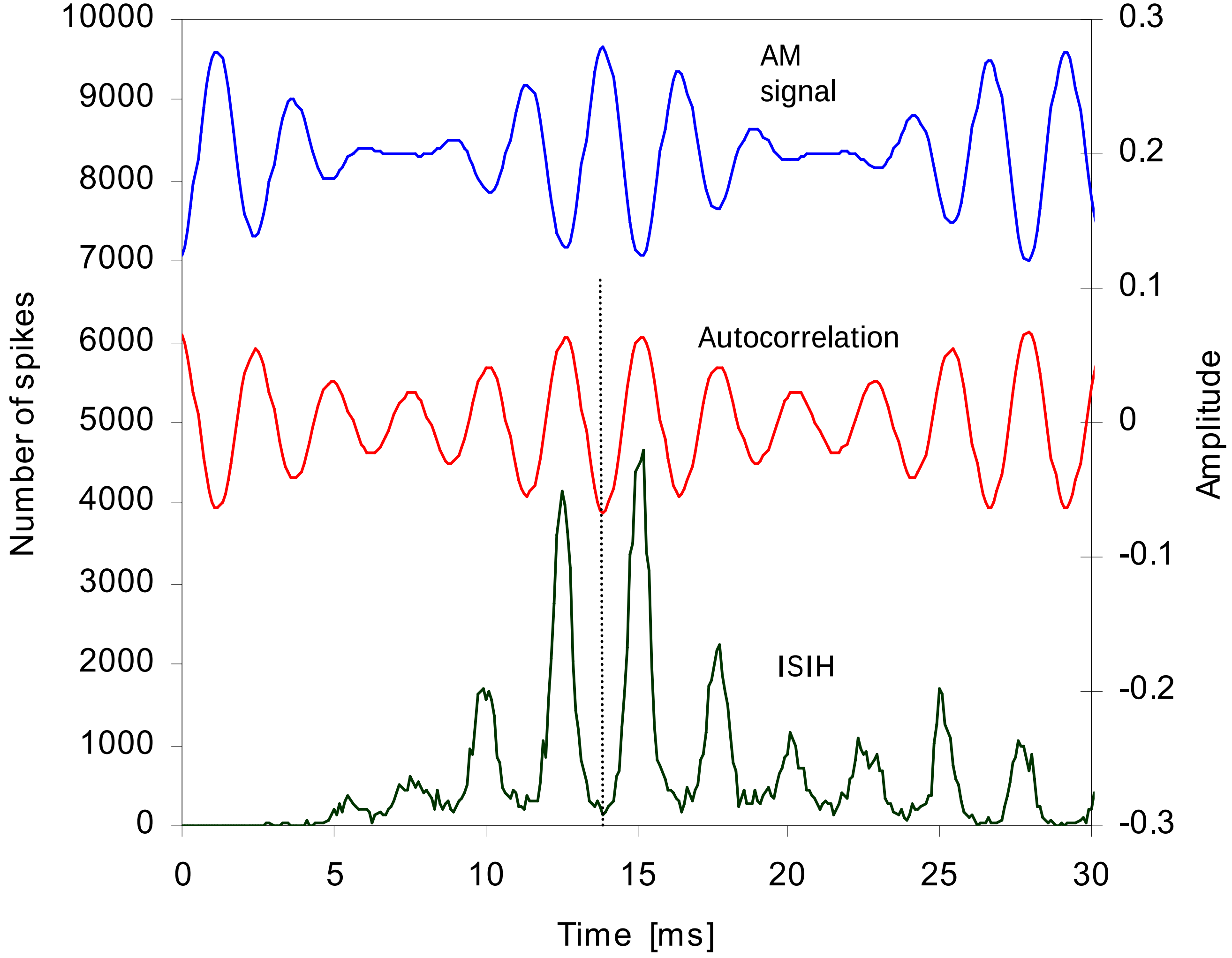
# Autocorrelation in the auditory nerve

JOURNAL OF NEUROPHYSIOLOGY
Vol. 76, No. 3, September 1996. *Printed in U.S.A.*

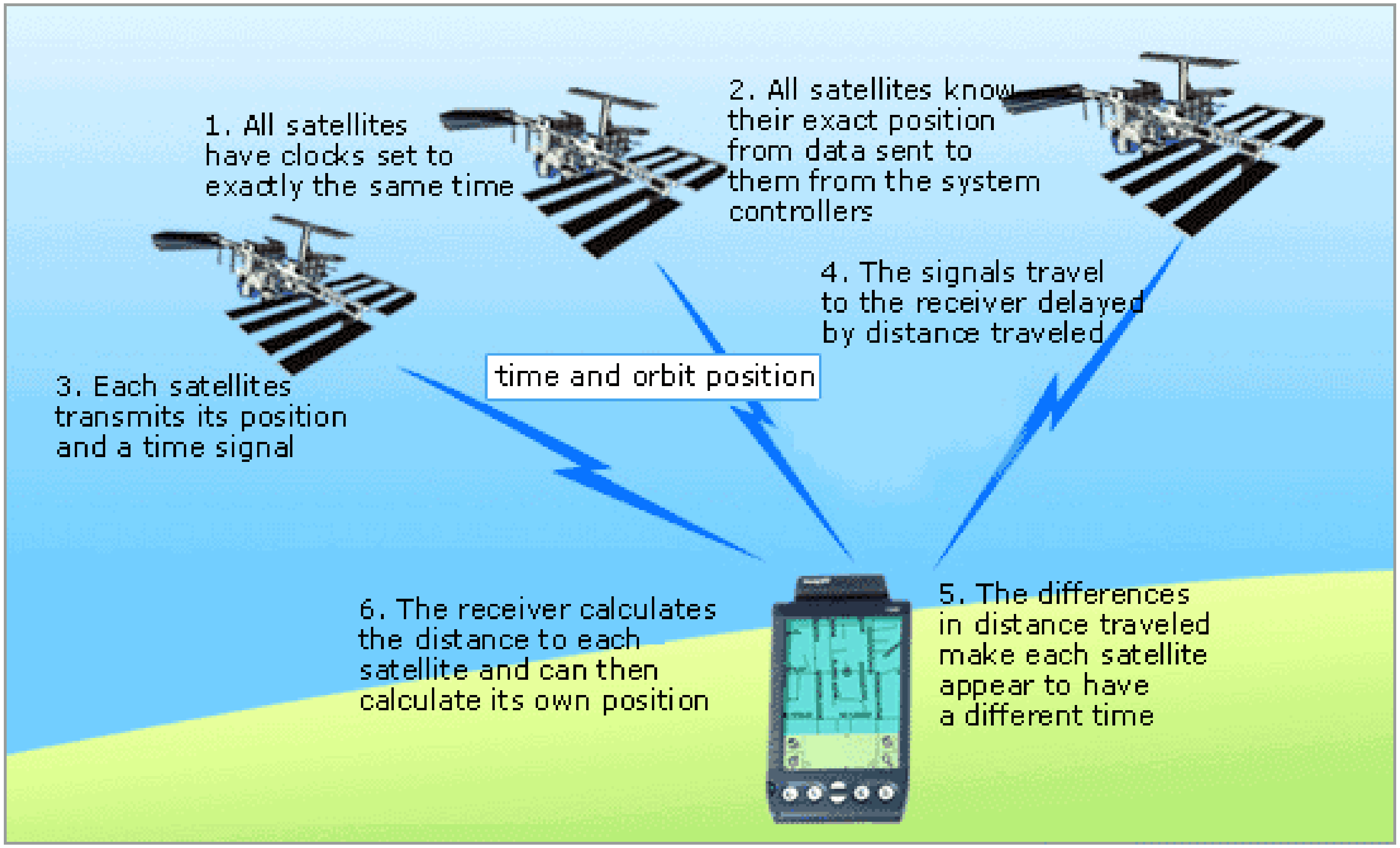
## Neural Correlates of the Pitch of Complex Tones. II. Pitch Shift, Pitch Ambiguity, Phase Invariance, Pitch Circularity, Rate Pitch, and the Dominance Region for Pitch



# Pitch shift effect in a simulated spiking neuron



# Application: the Global Positioning System




Source: www.navicom.co.kr

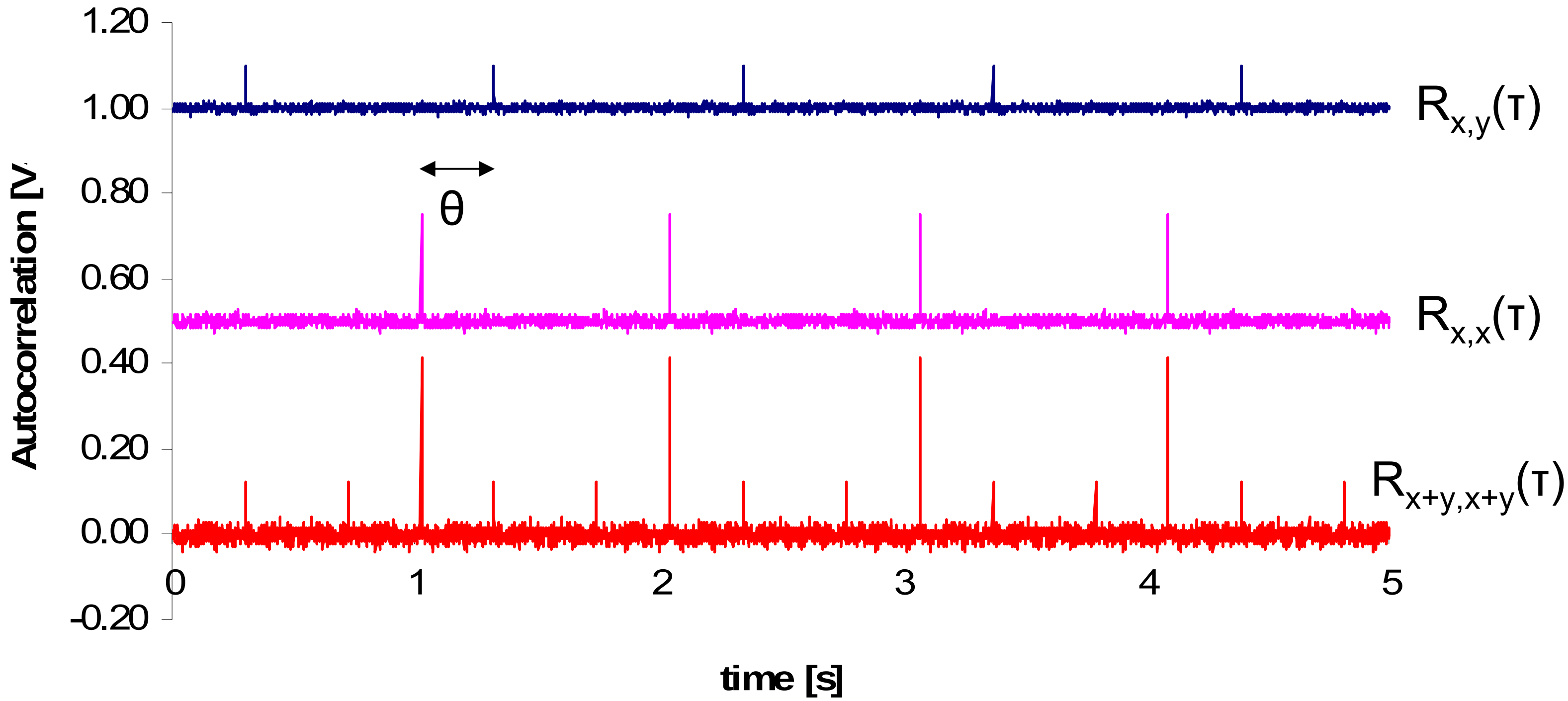
# GPS Signals: Pseudorandom codes

- Binary serial codes
- Designed to have noise-like character:
  - Sharp autocorrelation peaks
  - Near orthogonality between codes
- Usually created with linear feedback shift registers
- Many types
  - maximum length sequences
  - Gold codes
  - Kasami codes
  - Welch codes
- Gold codes – 1023 bits, used in GPS C/A mode

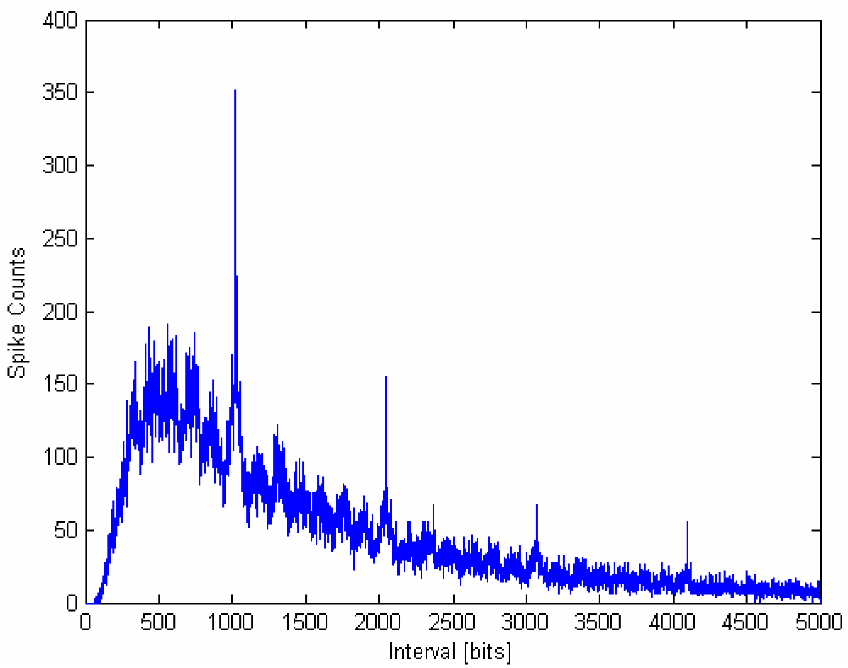
# Cross-correlation functions of Gold codes

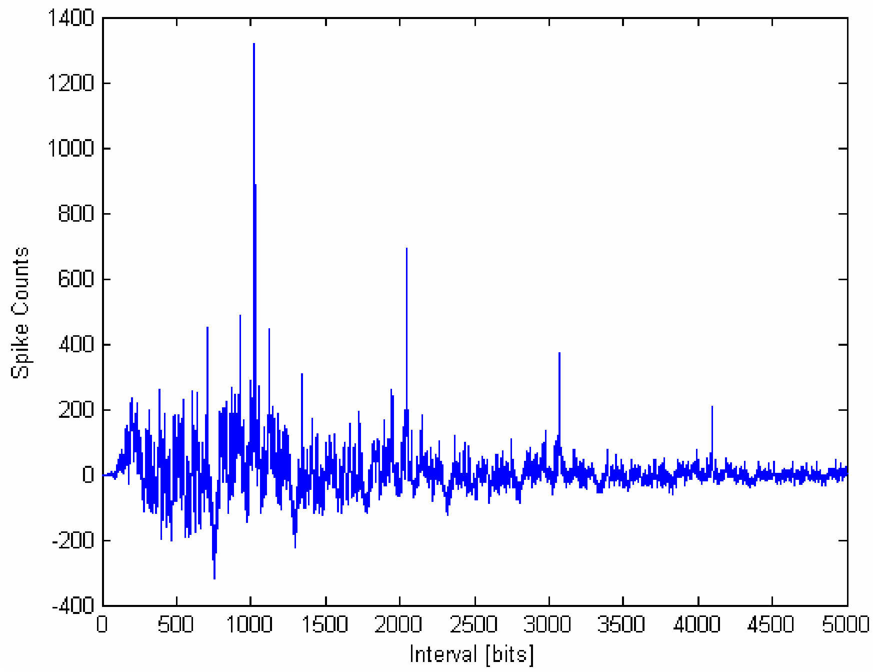
$X=G_1(t)$

$Y=G_1(t+\theta)+G_2(t)$

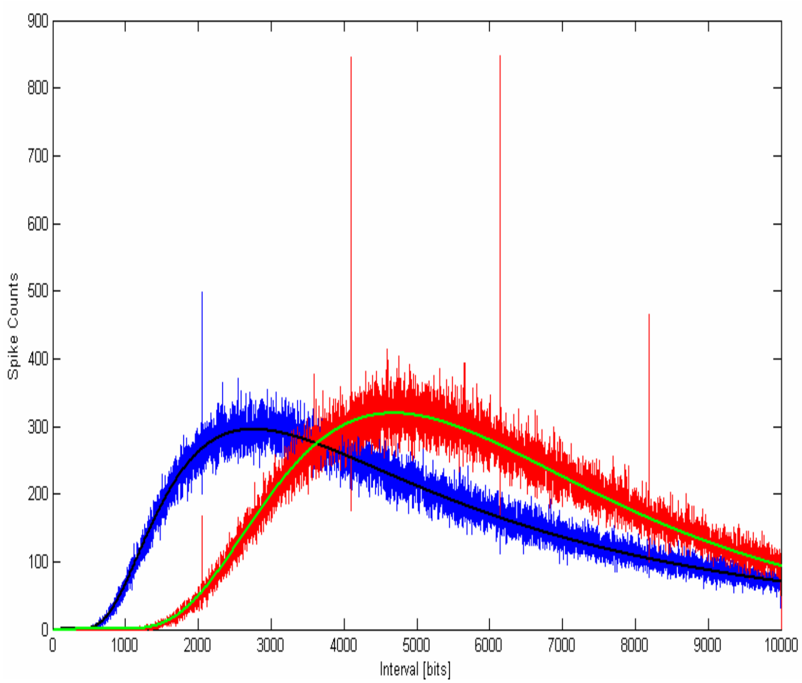


# Autocorrelation functions of Gold codes: ISIHs

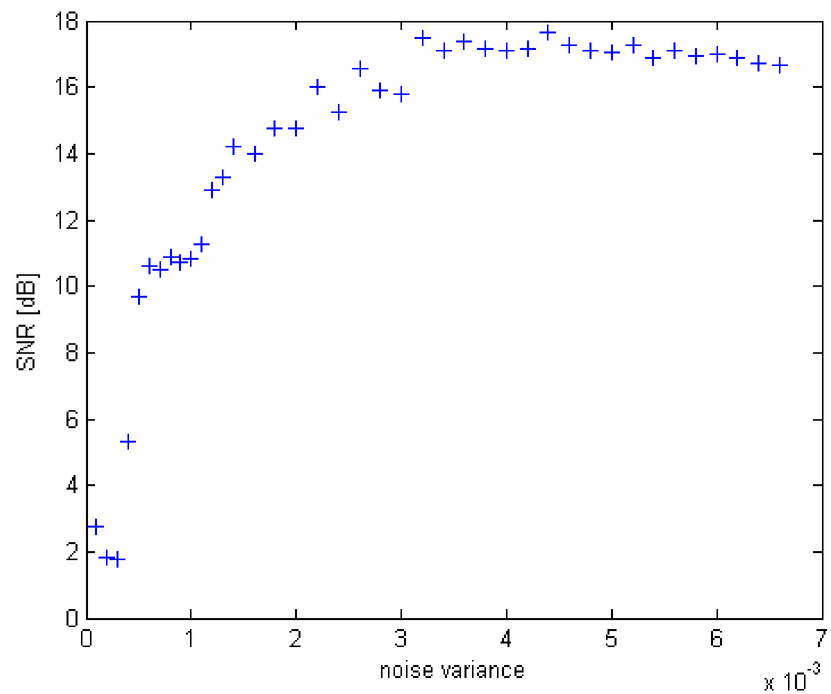


# Tuning with Noise and Drift



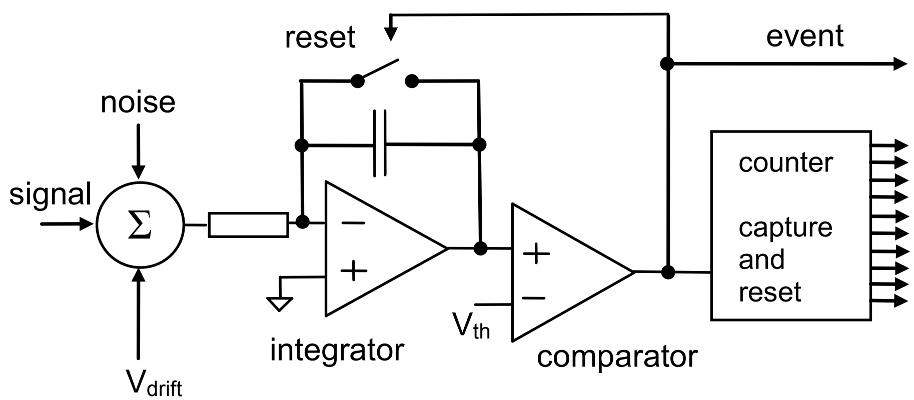

Different drift terms

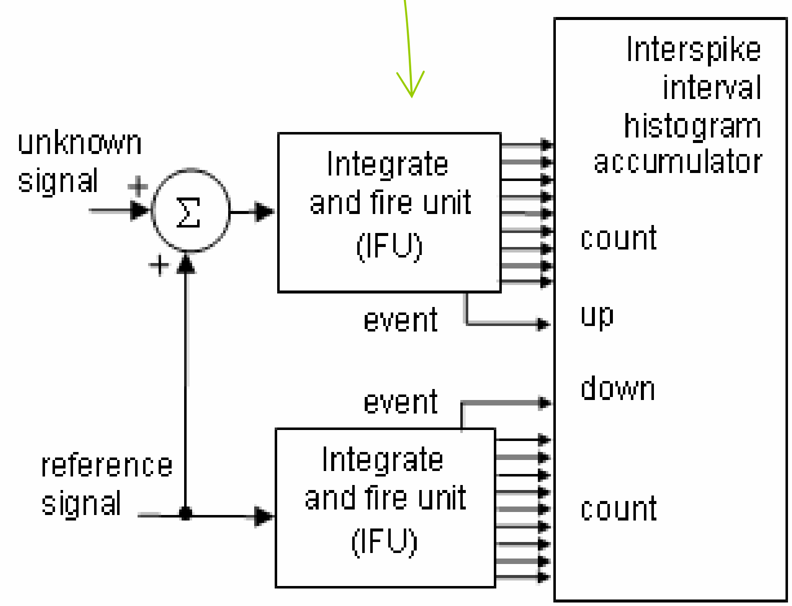



Different noise

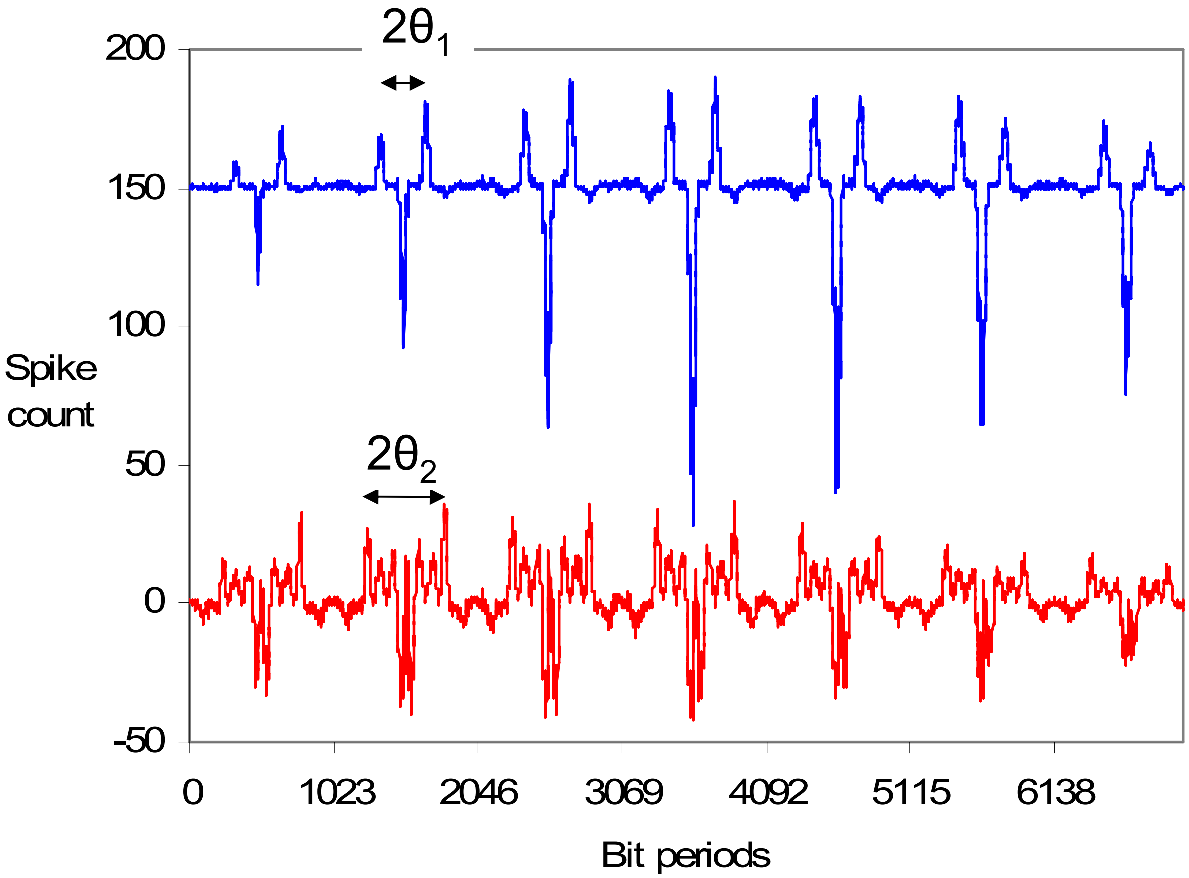
(stochastic resonance)

# Circuits

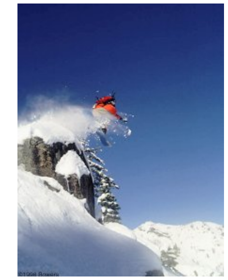

reset
event
noise
signal
Σ
counter
capture
and
reset
integrator
$V_{th}$
comparator
$V_{drift}$

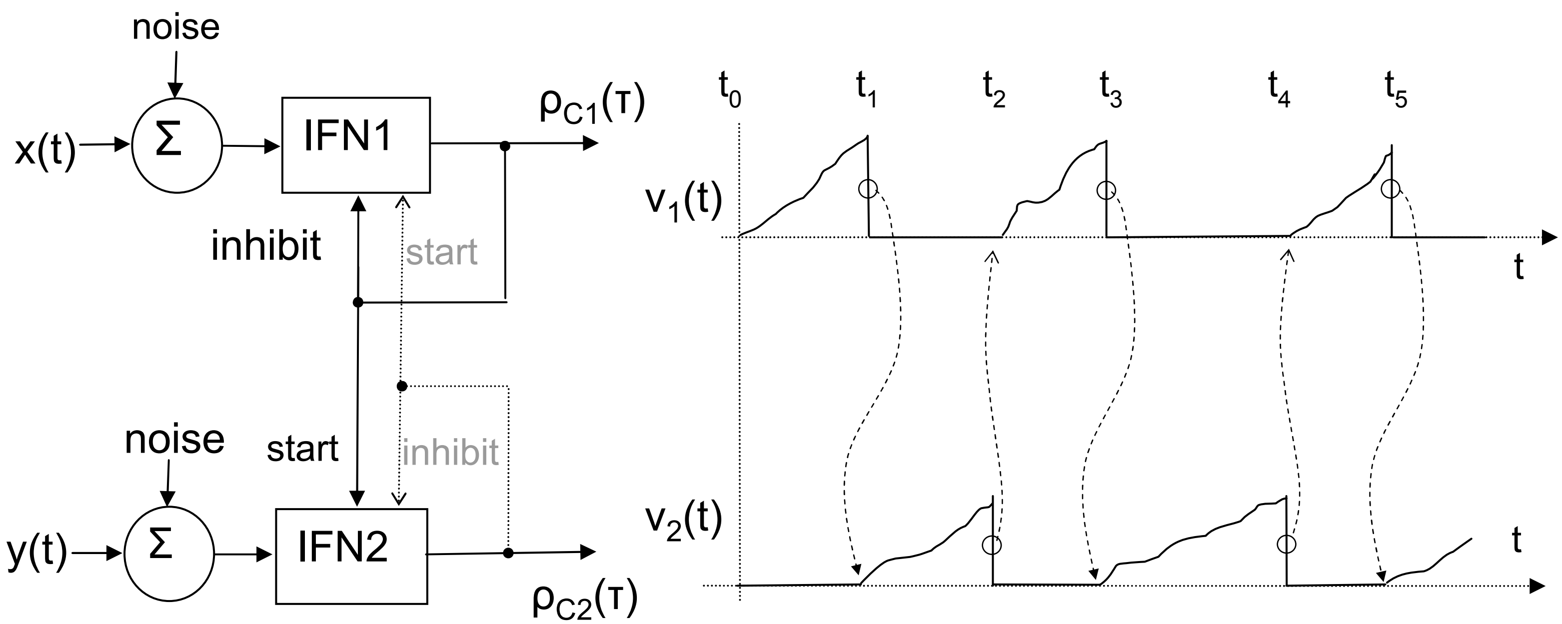

Interspike
interval
histogram
accumulator
unknown
signal
Σ
Integrate
and fire unit
(IFU)
count
event
up
down
event
reference
signal
Integrate
and fire unit
(IFU)
count

# Circuit Output

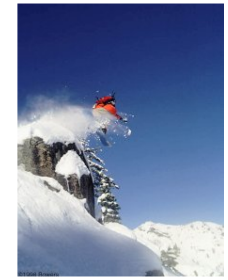


# A cross-correlation circuit





# Why does it work?



$$q_{t_2(IFN2)-t_1(IFN1)}(\tau) = \{\text{Probability that in sequence } [t_{0(IFN2)}, t_{1(IFN1)}, t_{2(IFN2)}],\ t_2 \text{ and } t_1 \text{ are separated by } \tau\}$$

$$= \int_{t_0}^{\infty} \rho_{C2}\left(t_1 + \tau \middle| t_1\right) \rho_{C1}\left(t_1 \middle| t_0\right) dt_1$$

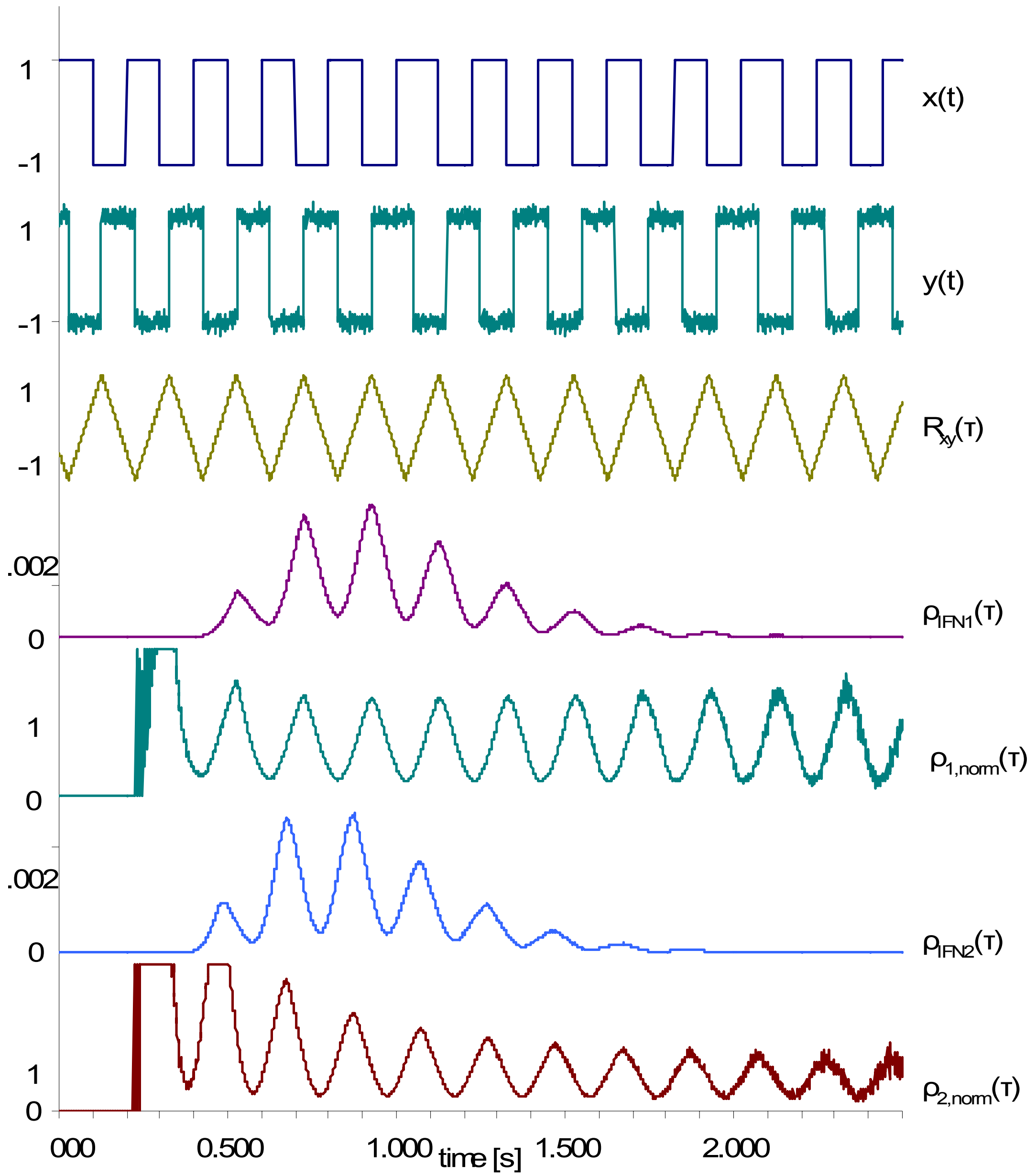
$$= \int_{t_0}^{\infty} \rho(\tau)\rho(t_1 - t_0)(1 + wy(t_1 + \tau))(1 + wx(t_1))dt_1$$

$$= \int_{t_0}^{\infty} \rho(\tau)\rho(t_1 - t_0)dt_1 + w\int_{t_0}^{\infty} \rho(\tau)\rho(t_1 - t_0)y(t_1 + \tau)dt_1$$

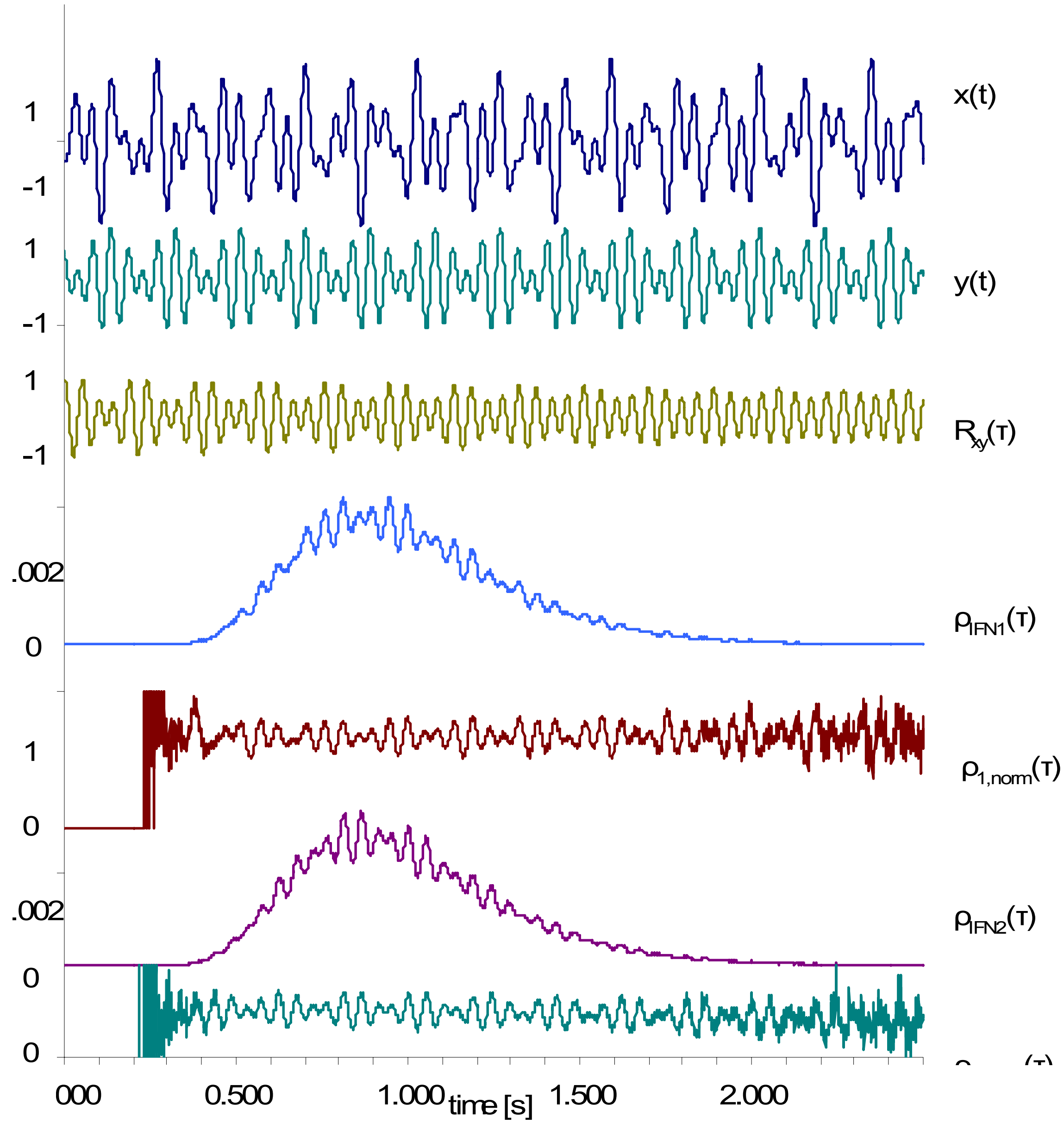
$$+ w\int_{t_0}^{\infty} \rho(\tau)\rho(t_1 - t_0)x(t_1)dt_1 + w^2\int_{t_0}^{\infty} \rho(\tau)\rho(t_1 - t_0)y(t_1 + \tau)x(t_1)dt_1$$

$$\approx \rho(\tau) + w^2\rho(\tau)\int_{t_0}^{\infty} y(t_1 + \tau)x(t_1)dt_1$$

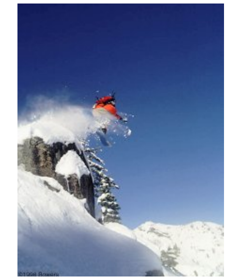
$$= \rho(\tau)\left(1 + w^2 R_{xy}(\tau)\right)$$

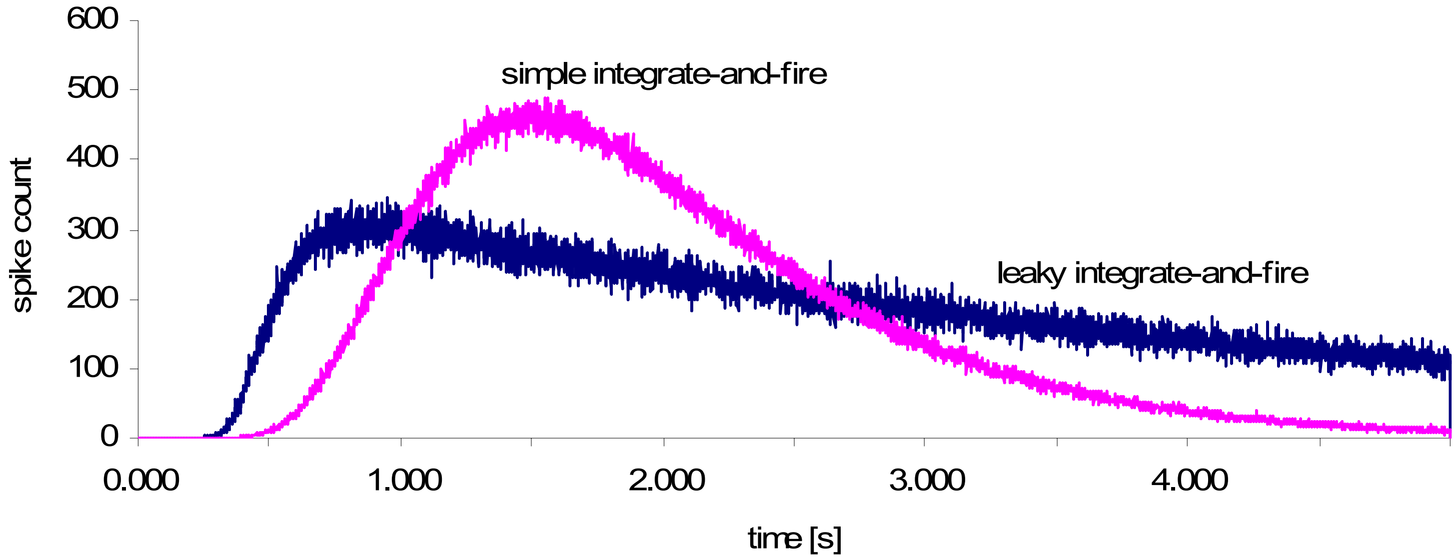


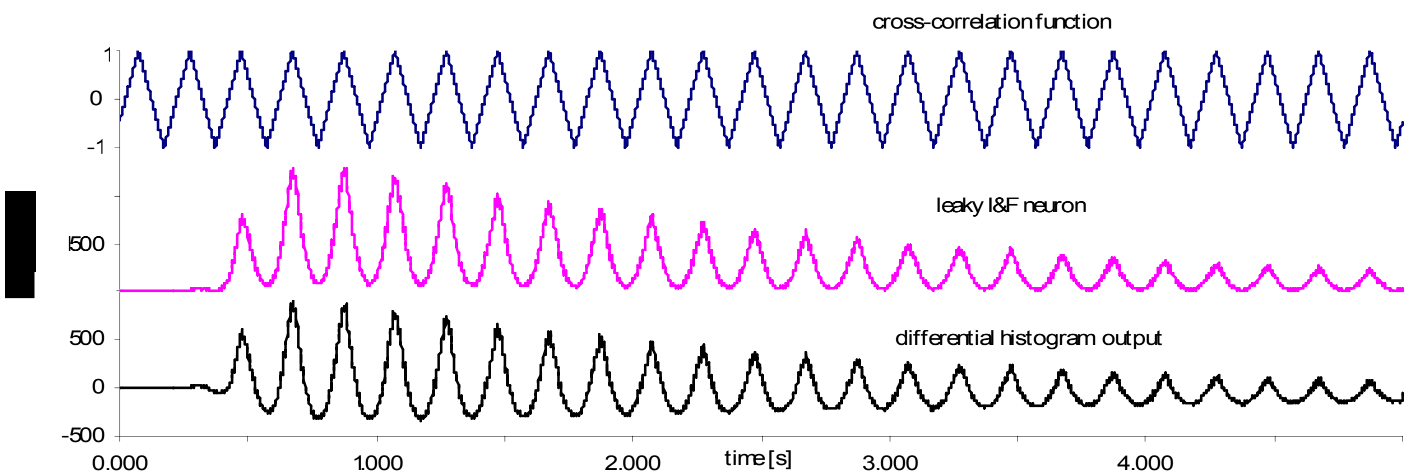
1
-1
x(t)
1
-1
y(t)
1
-1
Rxy(τ)
.002
0
ρIFN1(τ)
1
0
ρ1,norm(τ)
.002
0
ρIFN2(τ)
1
0
ρ2,norm(τ)
000
0.500
1.000
time [s]
1.500
2.000

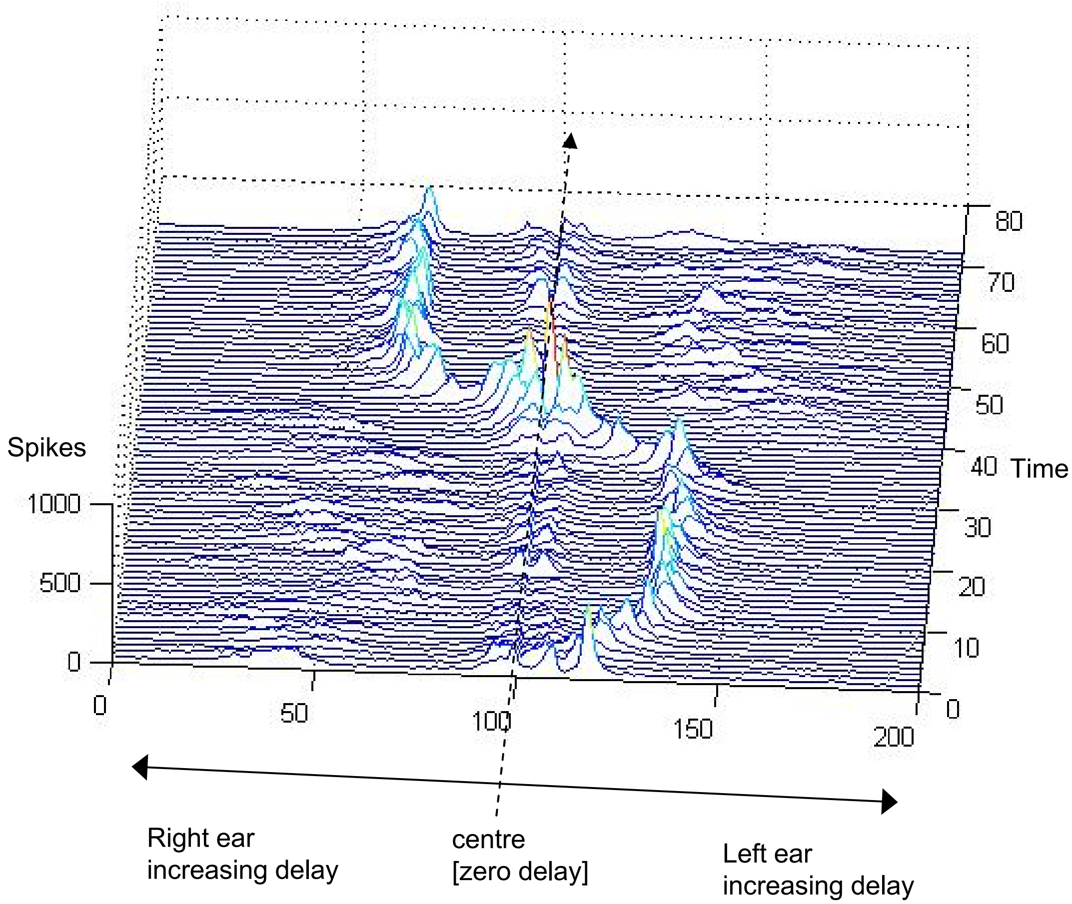
x(t)
y(t)
Rxy(τ)
ρIFN1(τ)
ρ1,norm(τ)
ρIFN2(τ)
1
-1
1
-1
1
-1
.002
0
1
0
.002
0
0
000
0.500
1.000
time [s]
1.500
2.000

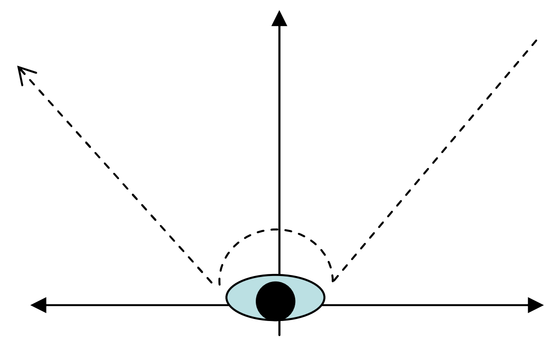




simple integrate-and-fire
leaky integrate-and-fire
spike count
600
500
400
300
200
100
0
0.000
1.000
2.000
3.000
4.000
time [s]

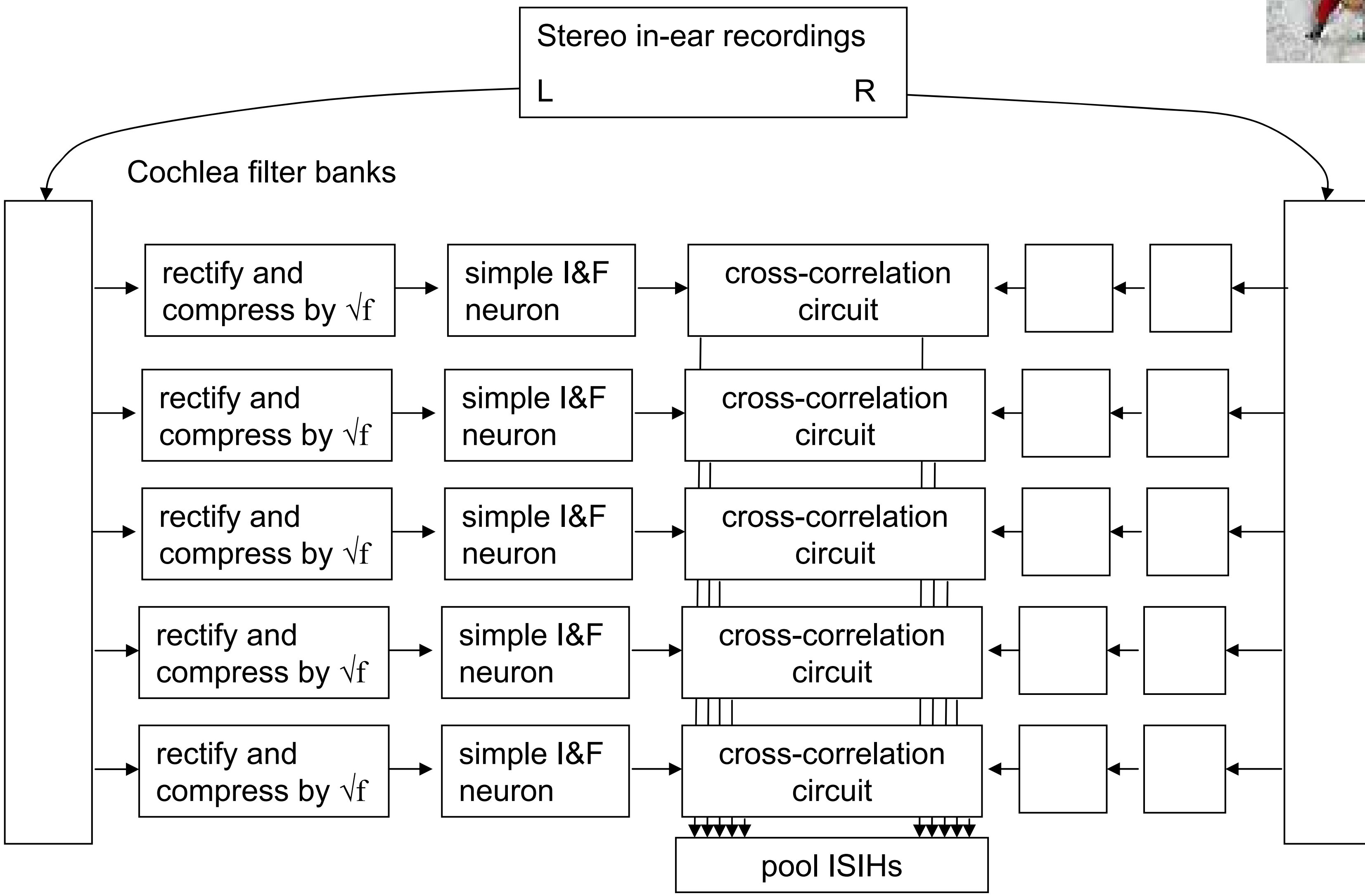

cross-correlation function
1
0
-1
[redacted]
leaky I&F neuron
500
differential histogram output
500
0
-500
0.000
1.000
2.000
time [s]
3.000
4.000

# Interaural Time Difference Detection

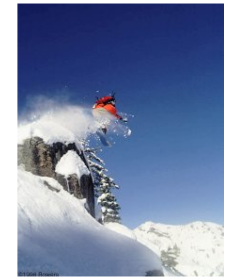


# Circuit


Stereo in-ear recordings
L
R
Cochlea filter banks
rectify and compress by √f
simple I&F neuron
cross-correlation circuit
rectify and compress by √f
simple I&F neuron
cross-correlation circuit
rectify and compress by √f
simple I&F neuron
cross-correlation circuit
rectify and compress by √f
simple I&F neuron
cross-correlation circuit
rectify and compress by √f
simple I&F neuron
cross-correlation circuit
pool ISIHs

# How many (neurons x spikes)?



$$q_{t_2(IFN2)-t_1(IFN1)}(\tau) = \{\text{Probability that in sequence } [t_{0(IFN2)}, t_{1(IFN1)}, t_{2(IFN2)}],\ t_2 \text{ and } t_1 \text{ are separated by } \tau\}$$

$$= \int_{t_0}^{\infty} \rho_{C2}(t_1 + \tau | t_1) \rho_{C1}(t_1 | t_0) dt_1$$

- This suggests that the second and subsequent spikes in a spike train are distributed with the p.d.f. modulated by the correlation function
- We can pool the results from an ensemble of correlators
- If we need *S* spikes to represent the function (*S* depends on the complexity of the function and the level of noise), we can use *N* neurons spiking *M* times each:

$$N \times (M-1) \geq S$$

# Implementation and detection of correlations: Conclusions

- If I&F neurons operate in a regime where they are not phase locked (=> small signal and some noise), then the ISIH has the form of the p.d.f. of the neuron with no signal, amplitude modulated by the autocorrelation function of the signal.
- The autocorrelation function which results is similar to that detected in mammalian auditory nerves in respect of pitch and several well-known psychoacoustic effects.
- Understanding the source of the stochastic autocorrelation effect allows us to design wide-range cross-correlators.
- The effect can be used to extract real-world signals such as the time delay between PRN coded signals in a GPS system, and possibly also interaural time delays.

# Local Feedback in Sensory Systems

- Why?
  - Improve sensitivity
    - Cochlear amplifier
  - Enable sensing
    - Saccadic eye movements
    - Haptic sensing
  - Control signal as variable
    - Interaural level differences

JC2

# Bigger picture: perception is an active process

Henri Poincaré, (1905). *La valeur de la science*. Paris: Flammarion. p. 47.

"To localize an object simply means to represent to oneself the movements that would be necessary to reach it. It is not a question of representing the movements themselves in space, but solely of representing to oneself the muscular sensations which accompany these movements and which do not presuppose the existence of space".

Rodney Brooks, (1986) "A Robust Layered Control System For A Mobile Robot", IEEE Journal Of Robotics And Automation, RA-2, April. pp. 14-23

“The world is its own best model.”

“Rodney Brooks,(1991) “Intelligence without representation,” Artificial intelligence 47, p 139-159.

“Representation is the wrong unit of abstraction in building the bulkiest parts of intelligent systems”

Kevin O’Regan and Alva Noë, (2001) “A sensorimotor account of vision and visual consciousness”, Behavioral and Brain Sciences 24(5) :

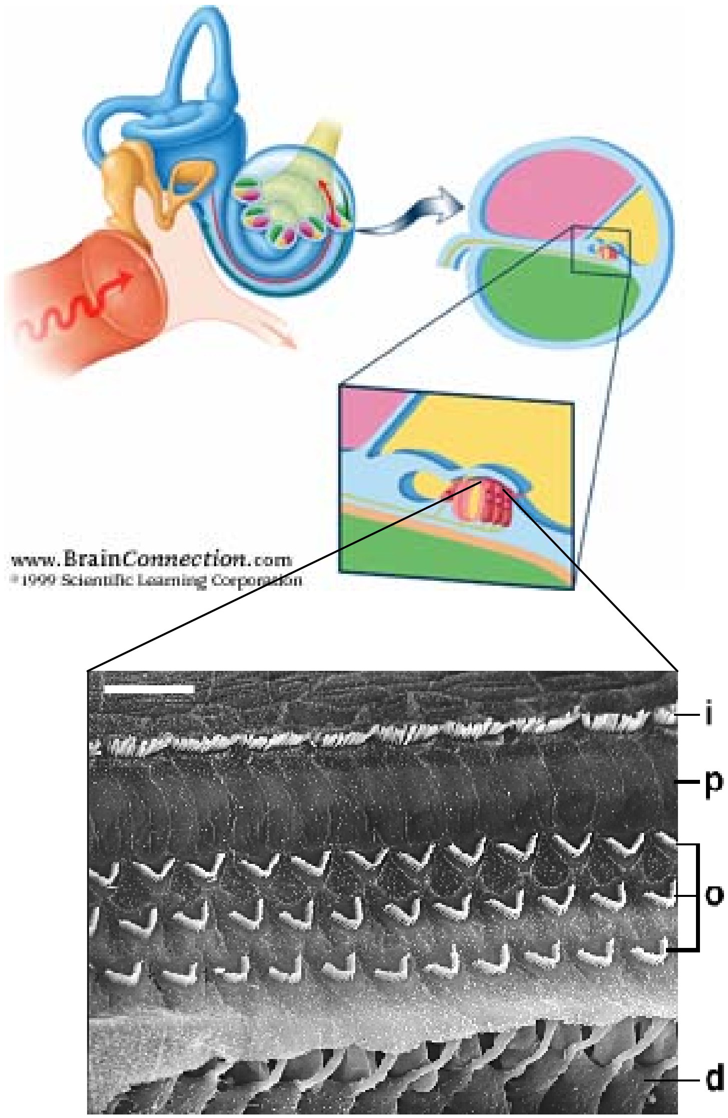
“Indeed there is no "*re*"-presentation of the world inside the brain: the only pictorial or 3D version required is the real outside version. What *is* required however are methods for probing the outside world -- and visual perception constitutes one mode via which it can be probed.”

**Slide 49**

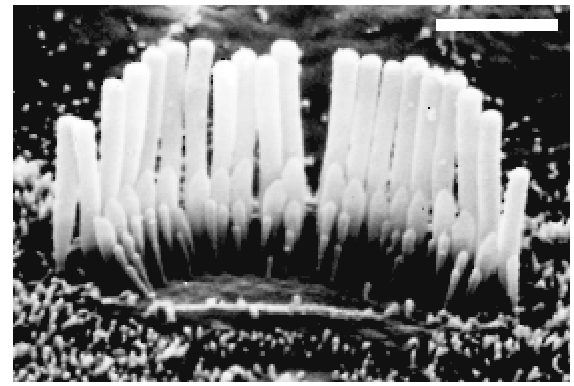
---

**JC2** Oregan: 529 citations
Brooks 91 2074 citations
Brooks 86 3789 citations
Tapson, 2007/06/26

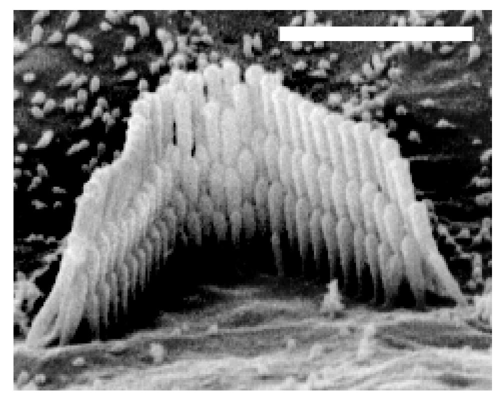
# The Cochlear Amplifier




Inner hair cells: sensors



Outer hair cells: actuators



# The Cochlear Amplifier

What we know about the cochlear amplifier:

- Its existence is inferred by the sensitivity of the cochlea and proven by the existence of otoacoustic emissions
- It appears to be implemented by electromechanical transduction in the outer hair cells

- What we don’t know about the cochlear amplifier:
  - Whether the OHCs act axially (Brownell - prestin electromotility - mammalian picture) or transversely (Hudspeth - amphibian picture)
  - How the OHCs increase the acoustic energy in the cochlea
  - What the OHCs “stand on” and what they “push against”
  - How the OHC motion phase-locks with the basilar membrane motion
  - Where the OHCs act, with respect to frequency on the longitudinal axis of the cochlea (and how amplifiers in different places couple together)
  - Whether the amplifier is self-tuned or open-loop

# Cochlea gain curves

M. A. Ruggero, Curr. Opin. Neurobiol. 2, 449 (1992).

- At CF, 77 dB range of input is compressed into 20 dB of output
- Far off CF, there is no compression

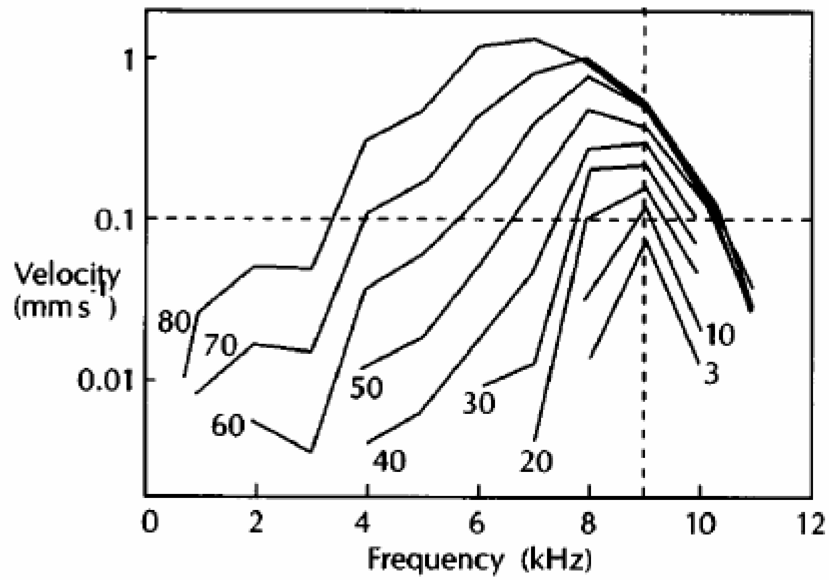
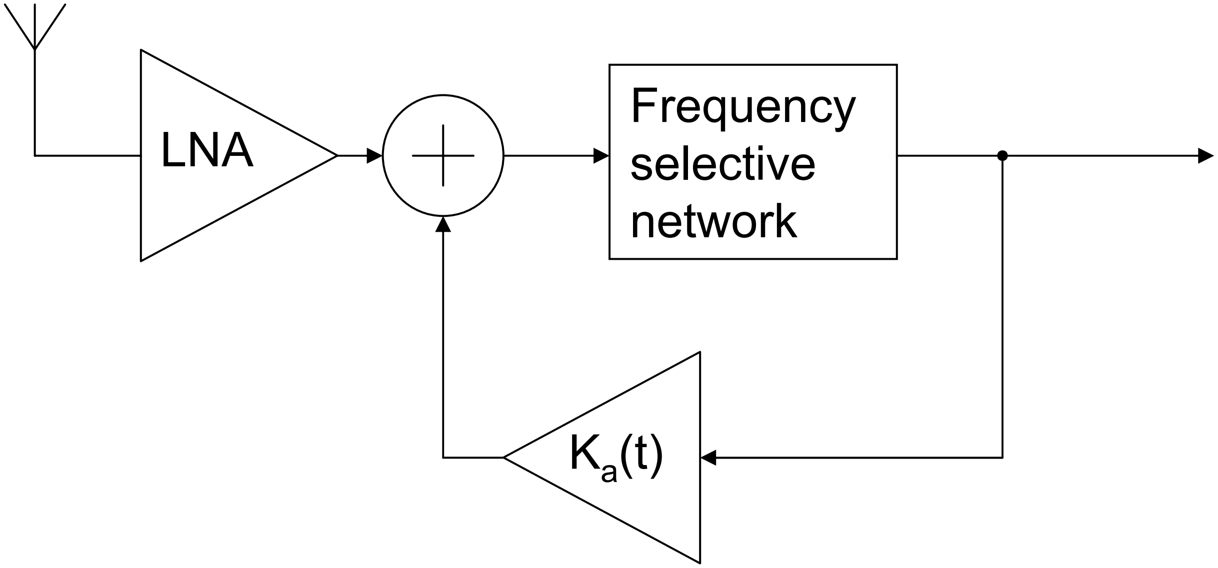



FIG. 1. Laser velocimetric data from a living chinchilla's cochlea displaying the root-mean-square velocity of one point on the basilar membrane as a function of driving frequency. Each curve represents a different level of stimulation, labeled in decibels sound-pressure level. The characteristic frequency at the position of measurement is 9 kHz. Notice that at 4 kHz, the curves from 40 to 80 dB span two decades (40 dB), whereas at 9 kHz the curves from 3 to 80 dB span just under one decade (20 dB). Note that the response at 9 kHz saturates beyond 60 dB. At 4 kHz, the response rises an average of 1 dB per decibel, whereas at 9 kHz the response rises only 0.3 dB per decibel. Note furthermore the dramatic increase in bandwidth as the intensity increases.

# Gold's Hypothesis: Regenerative Amplification

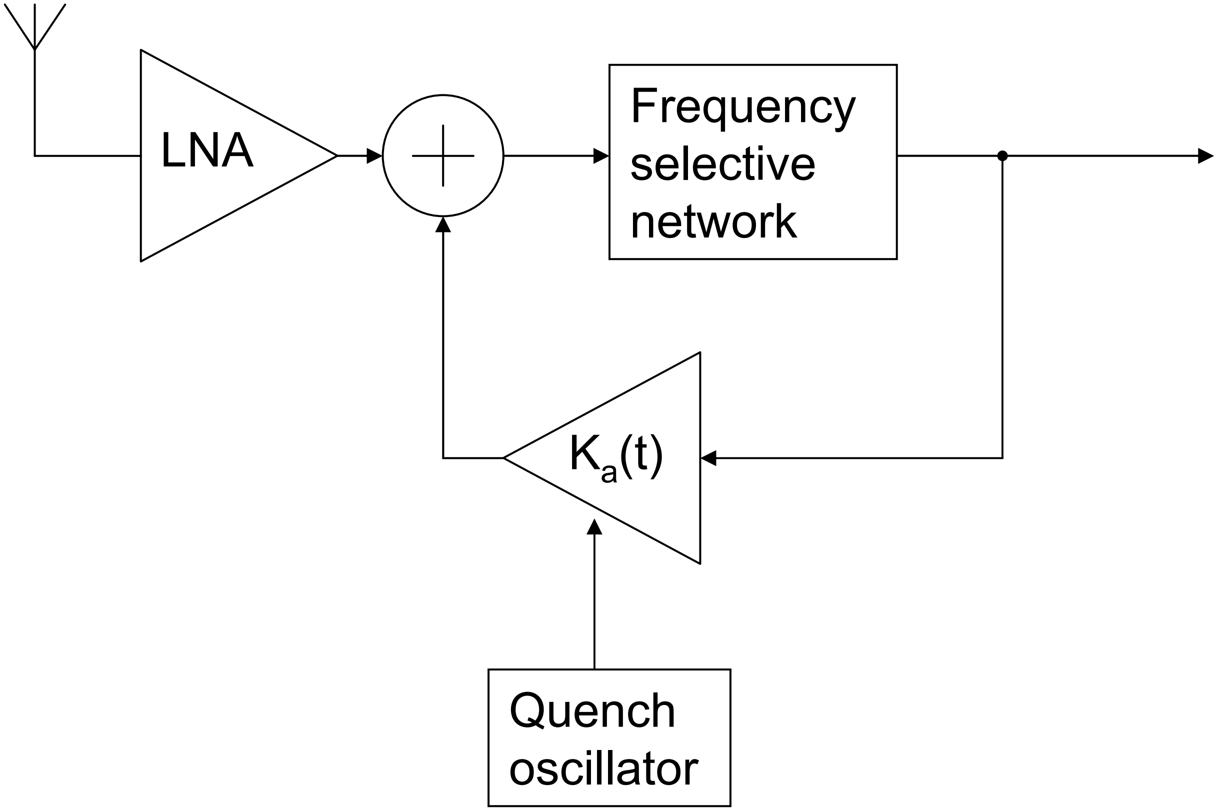
Gold, T. (1948). Hearing. II. The physical basis of the action of the cochlea. *Proc. Roy. Soc. Lond. B Biol. Sci.*, **135**, 492-498.

Gold, T. (1989). Historical background to the proposal 40 years ago of an active model for cochlear frequency analysis. In *Cochlear Mechanisms - structure function and models* Eds. J.P. Wilson, D.T. Kemp, Plenum Press, New York, 299-305.




Regenerative receiver (Edwin Armstrong 1911)

# Superregenerative receiver




Superregenerative receiver (Armstrong 1921)

# The Hopf Bifurcation Hypothesis

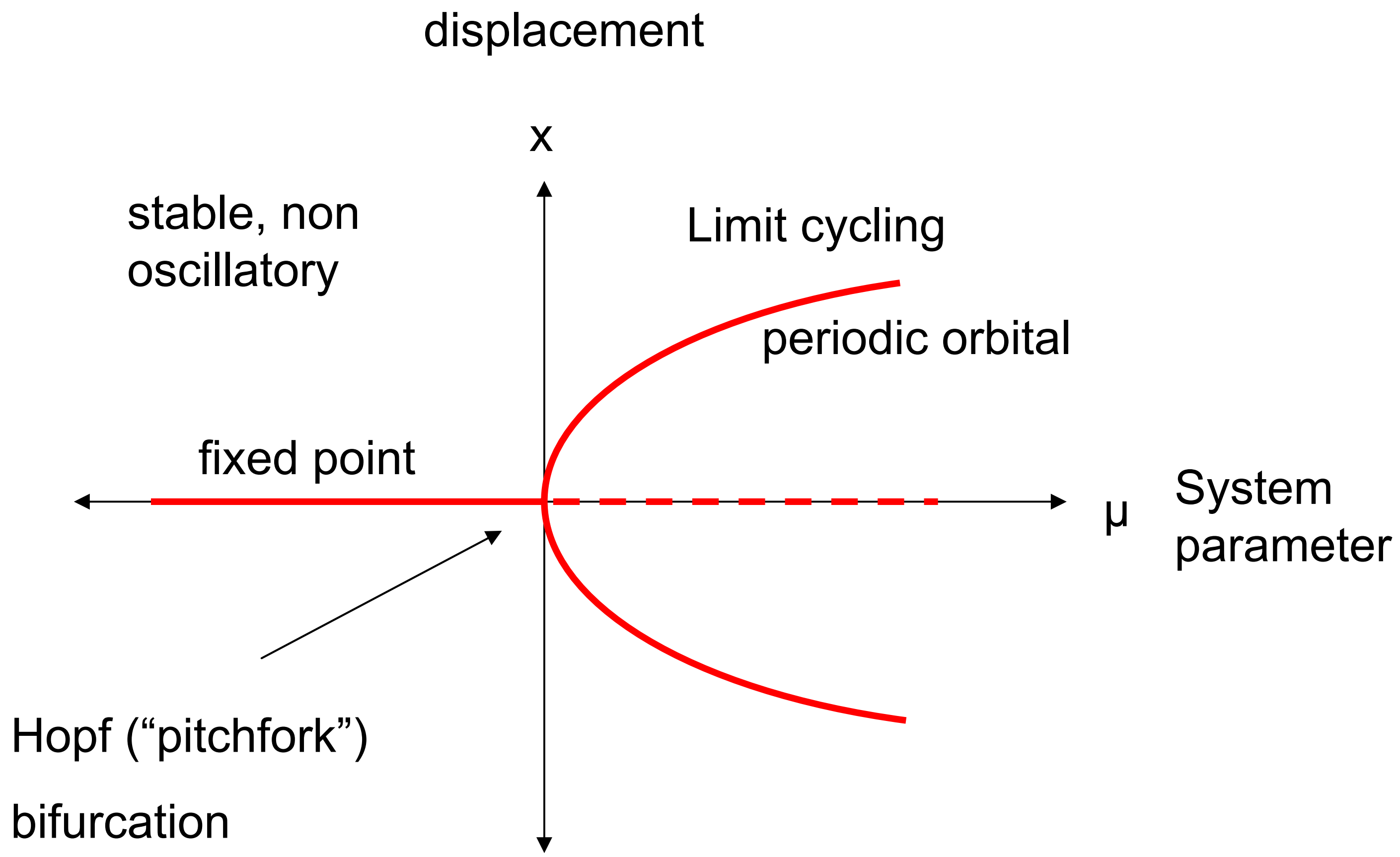
Bifurcation: a smooth change in system parameters causes a qualitative change in the state of stability.

Hopf bifurcation: (practically) the change is from a stable fixed point to a stable limit cycle. The change is smooth and reversible.

- Eguilez et al. (2000)
  - Nonlinear oscillator of form $$\frac{dz}{dt} = (\mu + i\omega_0)z - |z|^2 z + Fe^{i\omega t}$$
  - Where from?
    - Electrical amplifier on IHCs
    - Hair bundle oscillations

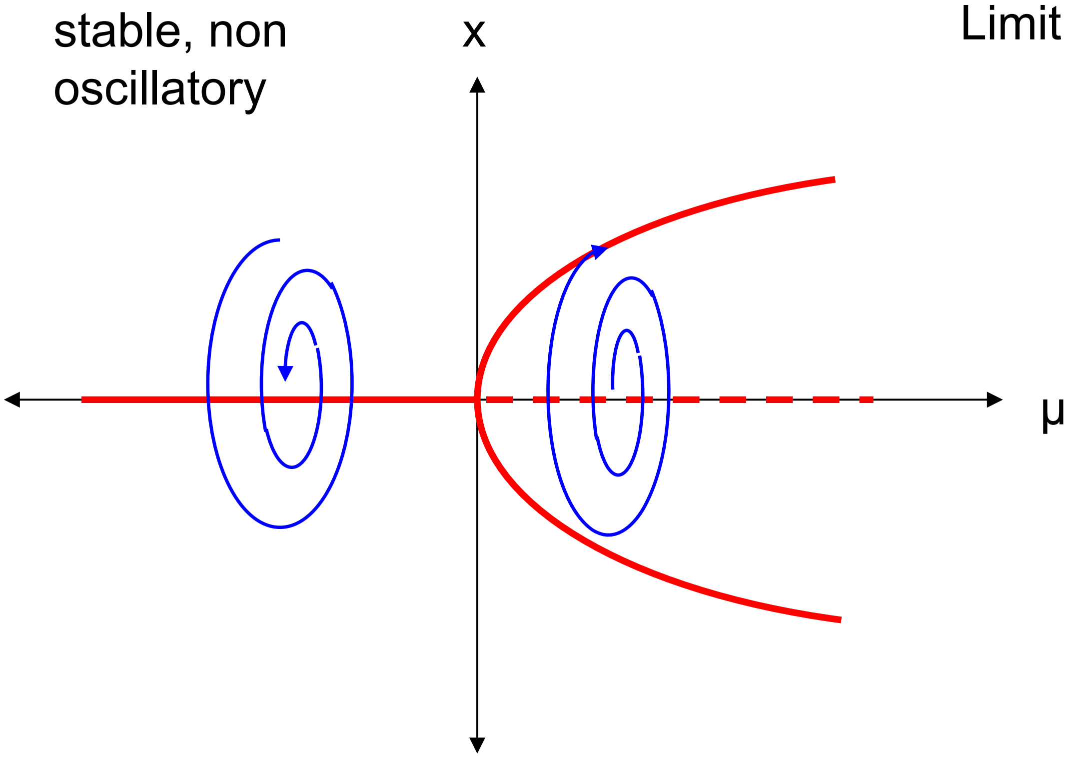
V. M. Eguíluz, M. Ospeck, Y. Choe, A. J. Hudspeth, and M. O. Magnasco, Essential Nonlinearities in Hearing, Phys. Rev. Lett., 84 (22), 5232-5235, 2000.

# Hopf Bifurcations and Supercritical Stability

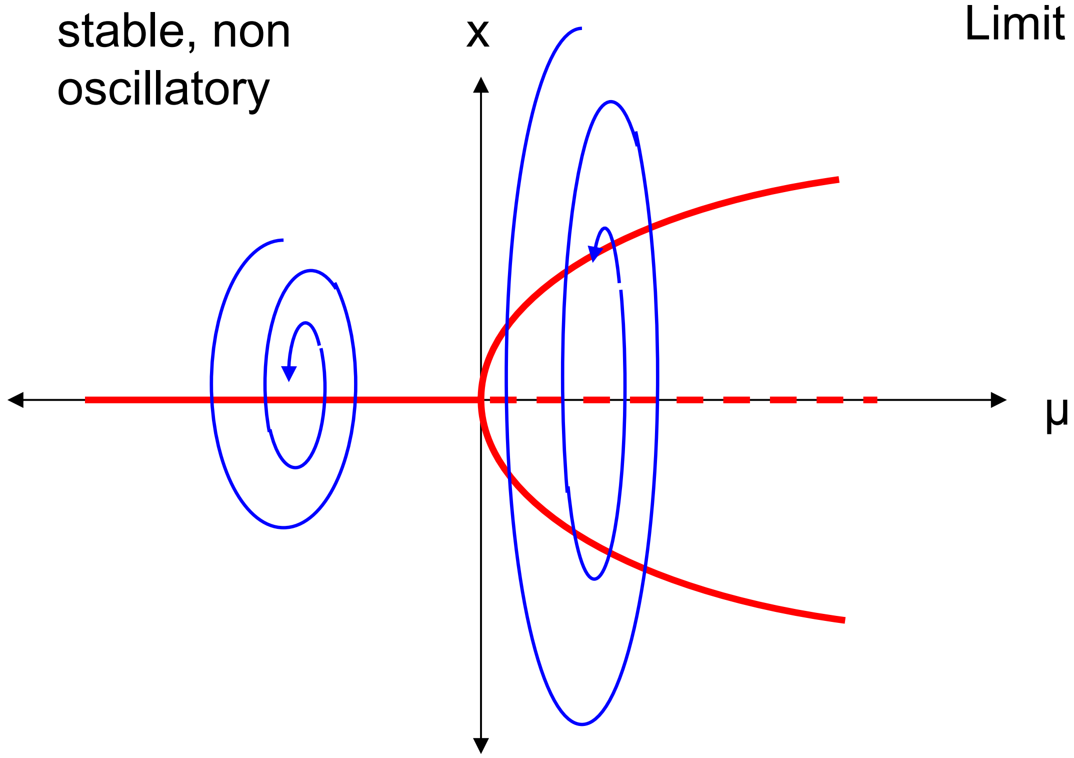


# Transients

- Phase plane



# Transients



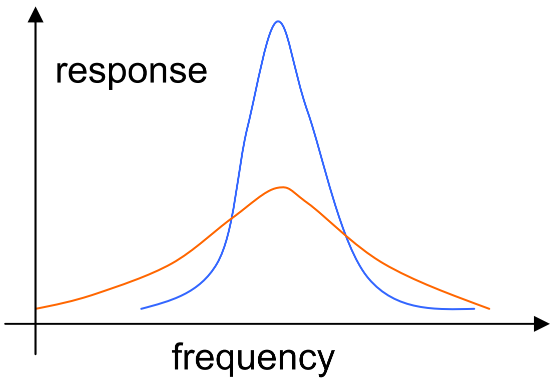
# The Hopf Bifurcation Hypothesis

- Camalet et al. (2000)
  - Same dynamics $$\frac{dz}{dt} = (\mu + i\omega_0)z - |z|^2 z + Fe^{i\omega t}$$
  - Self tuning feedback $$\frac{1}{\mu}\frac{\partial\mu}{\partial t} = \frac{1}{\tau}\left(\frac{z^2}{\delta^2} - 1\right)$$
  - Mechanism – dynein motor in kinocilium
- Kern and Stoop (2003)
  - Physiologically realistic coupling required for accurate reproduction of auditory nonlinearities.

# Digression: Sensors - Bandwidth and Q

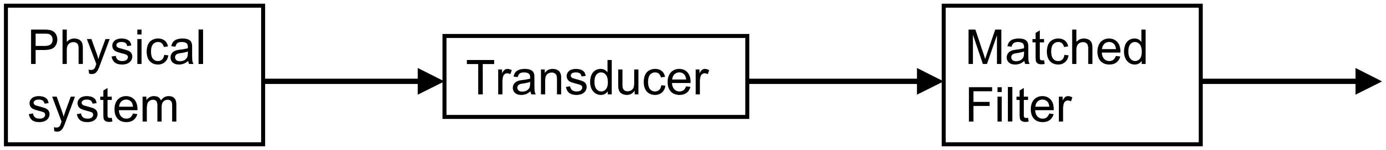
- Bandwidth of sensors is generally limited to reduce noise
  - Need to accommodate the signal carrier bandwidth and the transient response
- Sensors are often mechanically or electrically resonant to enhance response
- Resonant characteristic is expressed as Q
- Low Q => wide bandwidth, high noise
- High Q => narrow bandwidth, low noise

$$Q = \frac{\omega_o L}{R} = \frac{1}{2\varsigma(t)}$$



# Sensors as Matched Filters

- A sensor can be thought of as a transducer and matched filter combined together
- The designer has to make an *ab initio* decision on the filter characteristics, which is also affected by the physics of transduction
- The usual method is to make a wideband transducer followed by a narrowband filter



# Designer's Problem Statement

- Unless the signal characteristics are stationary, the matched filter must adapt according to signal strength

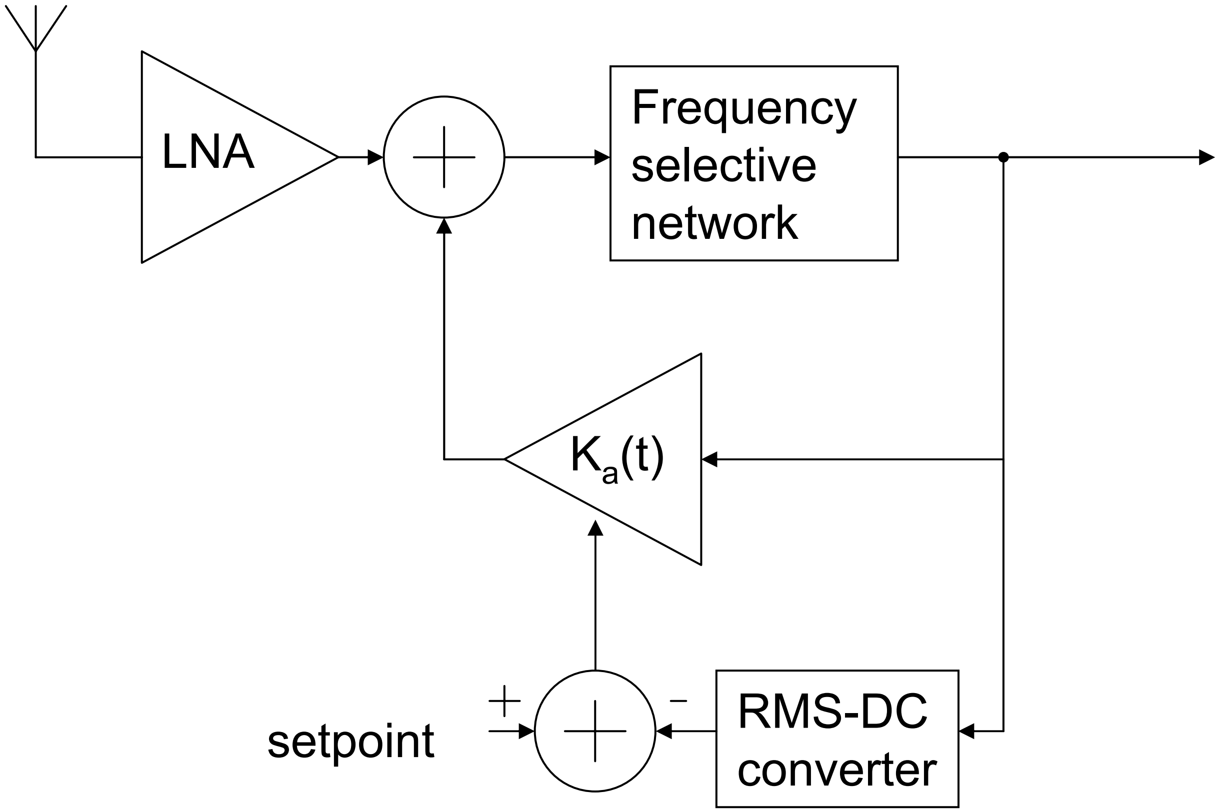
- Weak signal => narrow bandwidth filter

- Strong signal => wide bandwidth filter

- Note that bandwidth is a tradeoff:
  - Narrow bandwidth => slow transient response

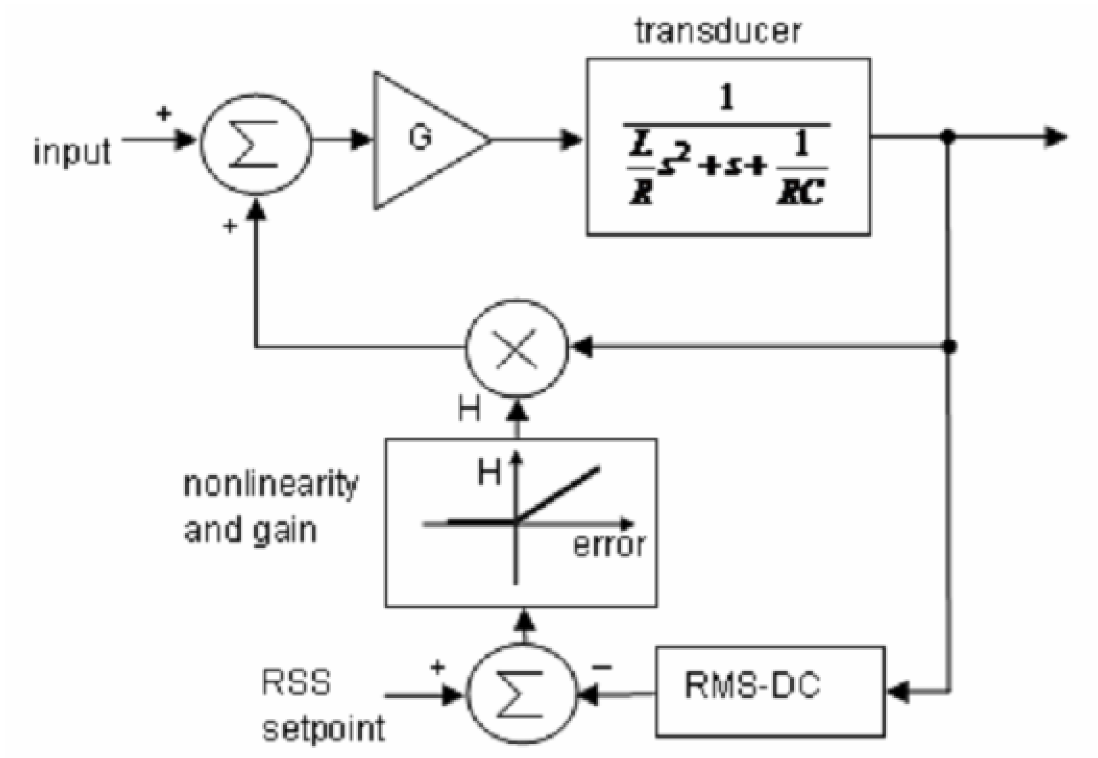
- It is assumed that Q x bandwidth is a constant

# Supercritically Regenerative Receivers

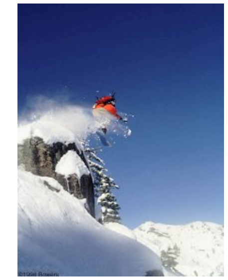



Supercritically stable receiver (Tapson 2006)

# Supercritical stability block diagram



# Transfer Function and Describing Function



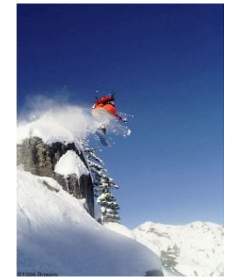
$$\frac{y(s)}{x(s)} = \frac{Gs}{\frac{L}{R}s^2 + (1 - GH)s + \frac{1}{RC}}.$$

$$N(A,\omega) = \frac{4}{\pi A}\left(k - y_{rms}(t)\right)$$

$$A = \frac{4}{\pi}\left(k - y_{rms}(t)\right)$$

$$\omega = \sqrt{\frac{1}{LC}}$$

# Resonant Quality Factor

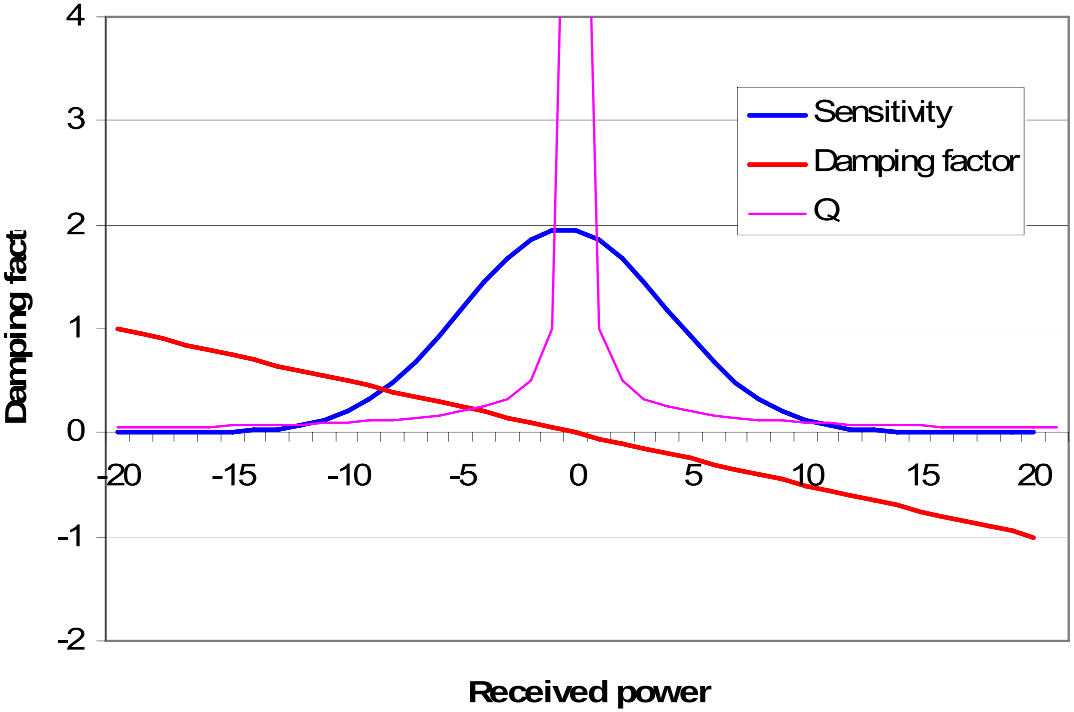


$$Q = \frac{\omega_o L}{(1 - GH(t))R}$$

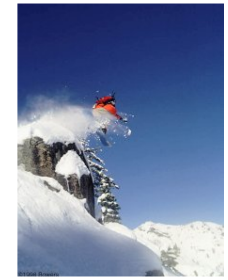
$$= \frac{1}{2\varsigma_0\left(1 - GH(t)\right)}$$

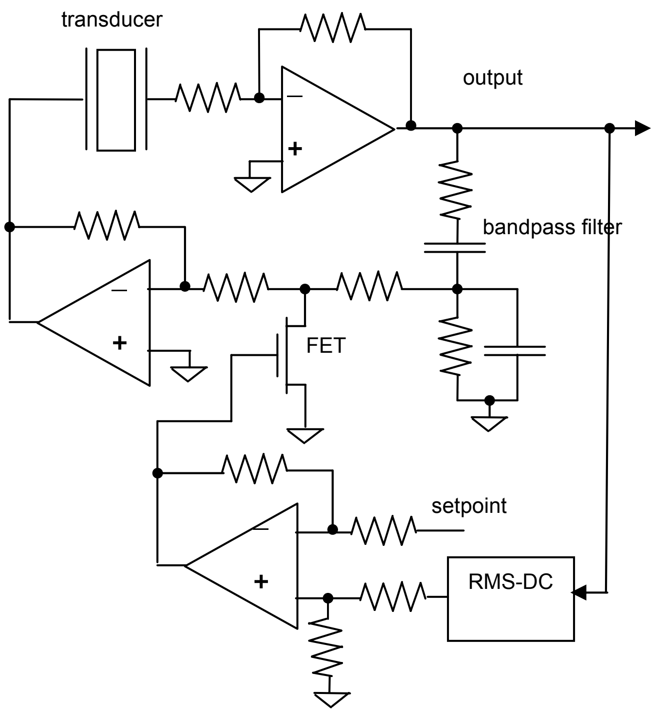
# Sensitivity

$$s(t) = e^{\omega_0 \int_{-\infty}^{E_p} \varsigma(\lambda) d\lambda}$$

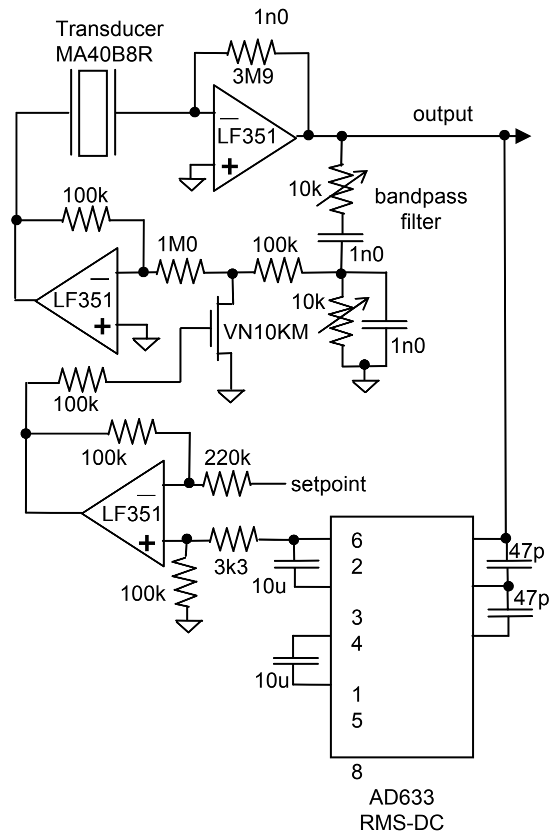


# Circuits

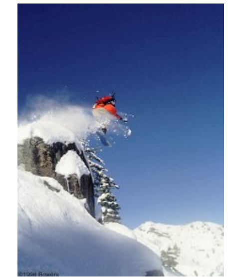




transducer
output
bandpass filter
FET
setpoint
RMS-DC

Transducer
MA40B8R
1n0
3M9
LF351
output
10k
bandpass
filter
100k
1M0
100k
1n0
LF351
10k
VN10KM
1n0
100k
100k
220k
setpoint
LF351
3k3
10u
100k
6
2
3
4
1
5
8
47p
47p
10u
AD633
RMS-DC



# Performance

- Can use correlation and coherence as measures of SNR

- Cross-correlation

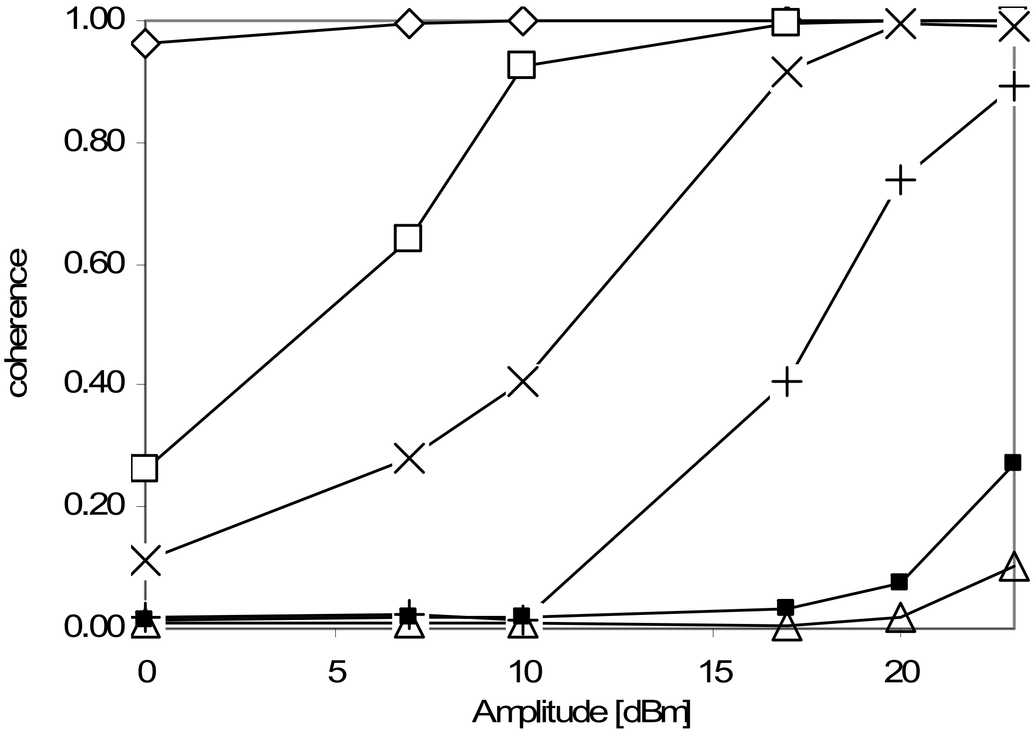
$$R_{XY}(\tau) = \int_{-\infty}^{\infty} x(t)y(t+\tau)dt$$

- Coherence

$$G_{XY}(f) = 2\int_{-\infty}^{\infty} R_{XY}(\tau)e^{-j2\pi\tau}.$$

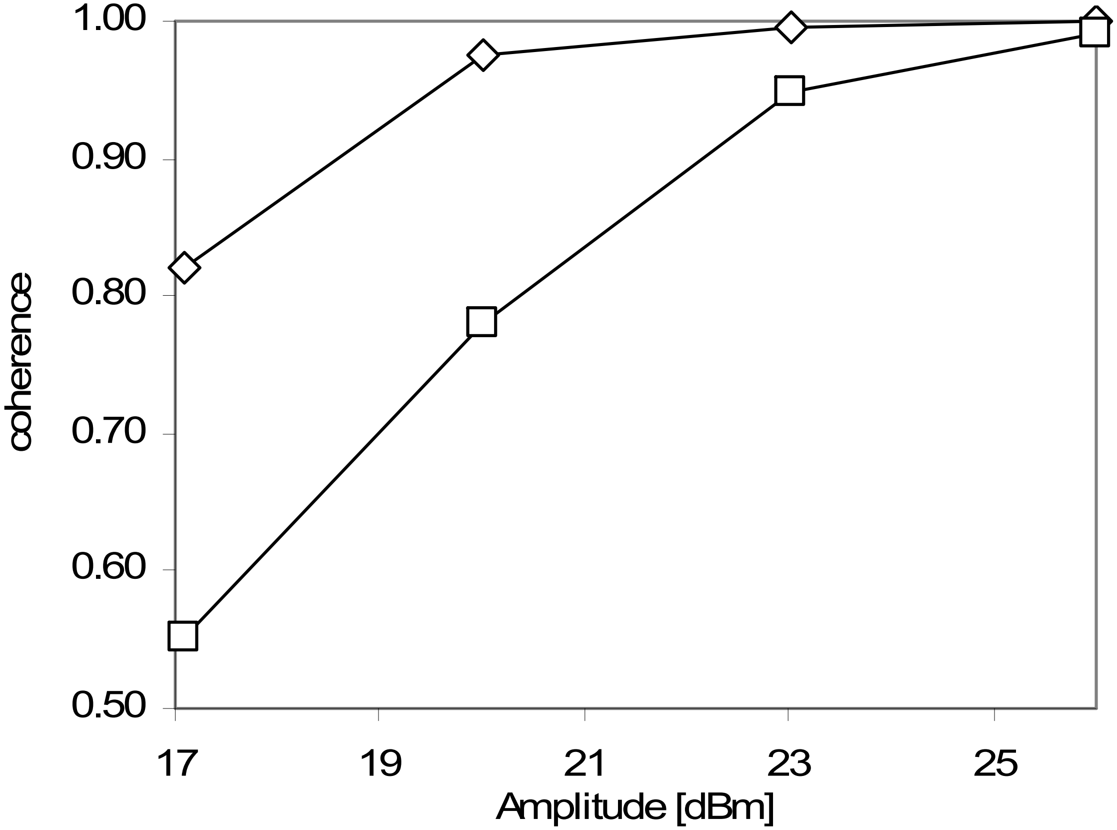
$$\gamma_{XY}^{2}(f) = \frac{\left|G_{XY}(f)\right|^{2}}{G_{XX}(f)G_{YY}(f)}$$

# Coherence – LRC sensor



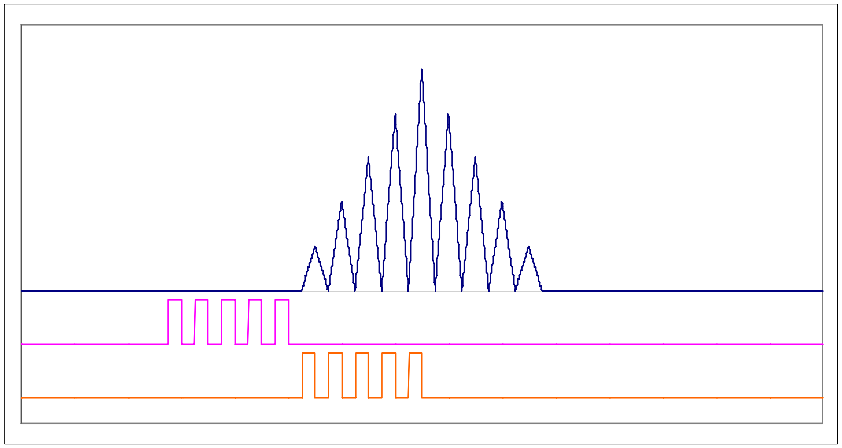

The uppermost curve (◊) represents the circuit detecting a signal at the resonant frequency. The coherence, even at 1dBm input, is 96%. By contrast, with the feedback disabled (□), the coherence drops to 26%. The lower four curves show closed-loop (CL) detection for input signals at 0.9 $f_r$ and 1.1 $f_r$, measured at the resonant frequency $f_r$ (+ and ×) and also at the input frequency (Δ and ■).

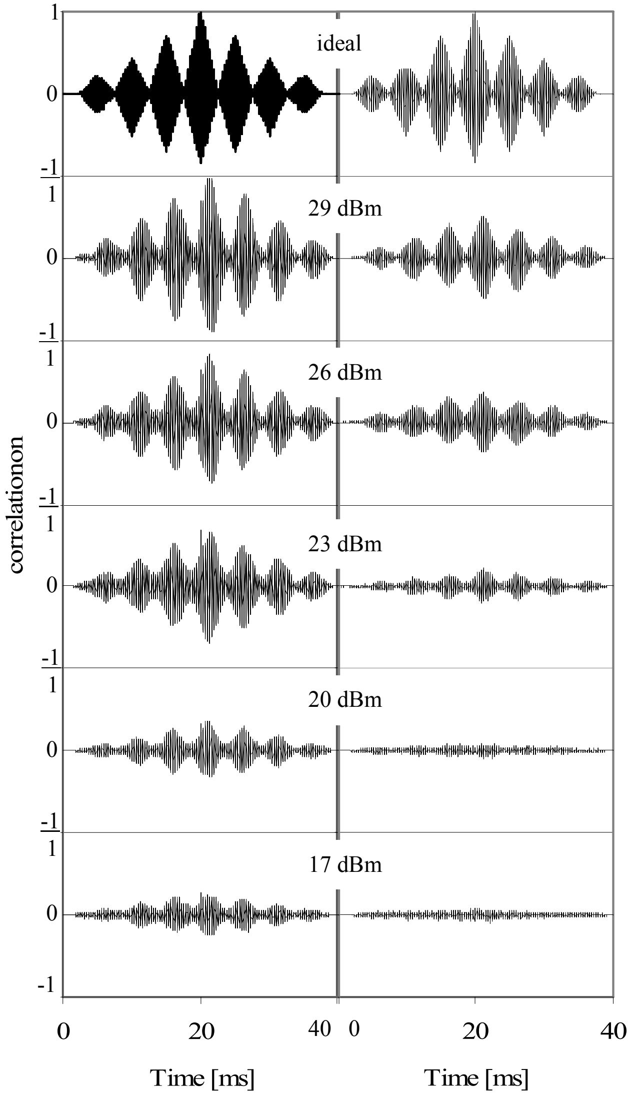
# Coherence – Sonar circuit



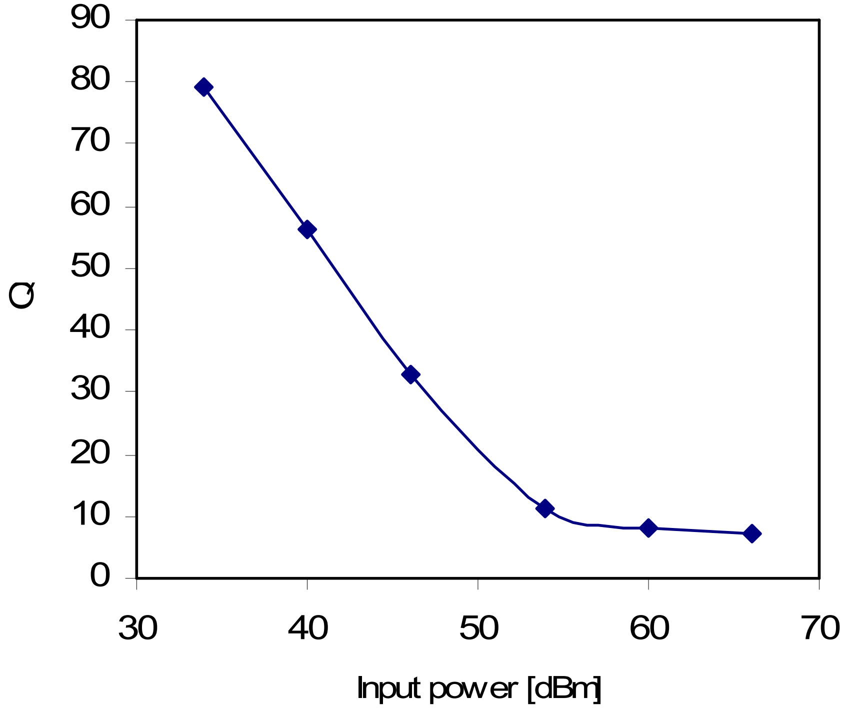
# Autocorrelation as a test of accuracy – sonar circuit

- Transducer driven with 50% duty cycle on-off keying (OOK)

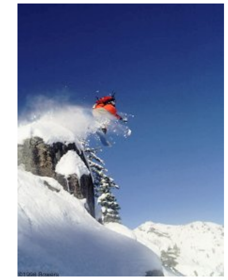


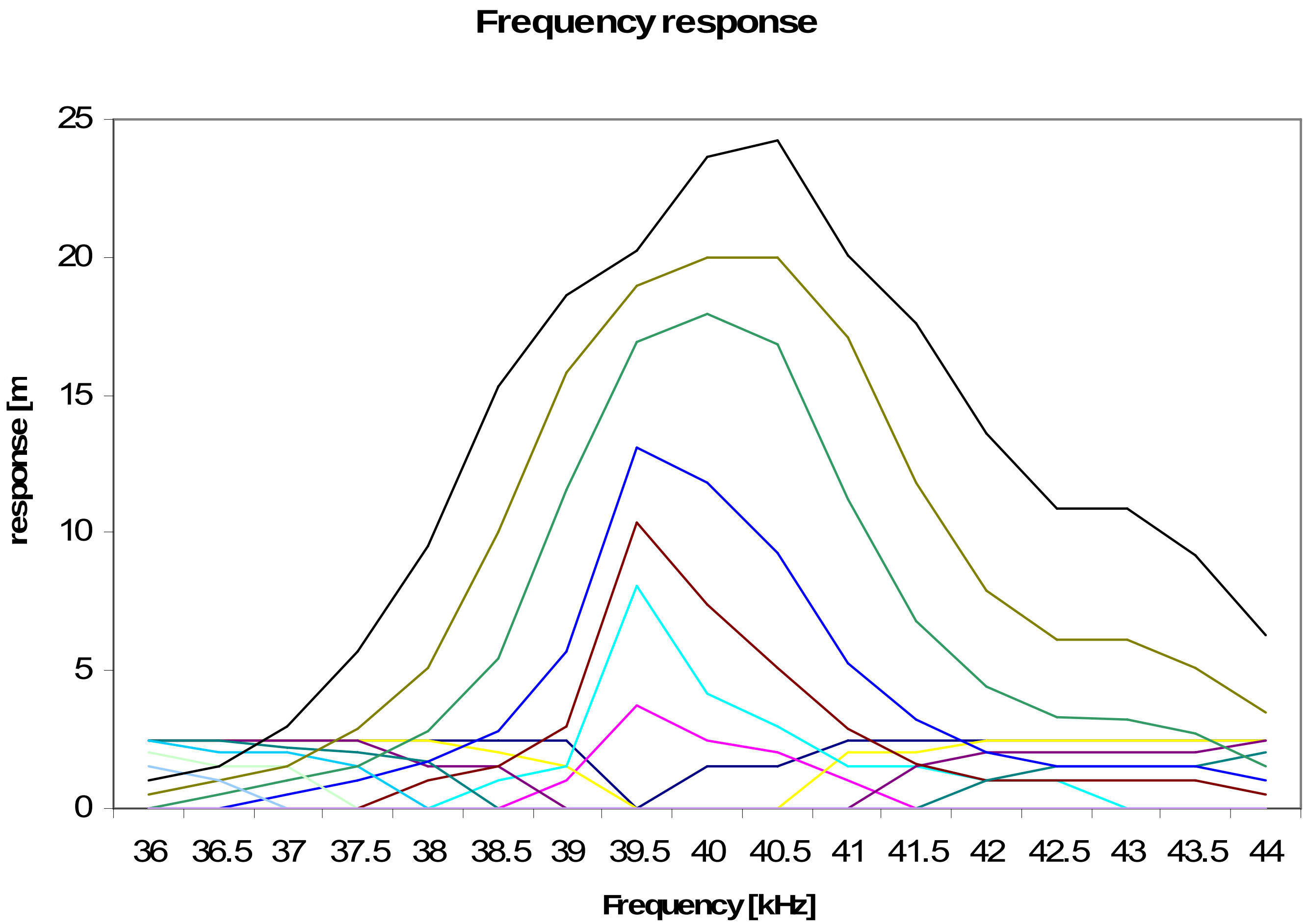


# Variation in Q – sonar circuit



# Variation in Q – sonar circuit (2)





# Supercritical stability: feedback in sensory systems
# Conclusions

- There is a growing consensus that the cochlear amplifier, and perhaps some other sensory systems, self-tune their sensitivity and may use regenerative feedback to add energy to the input signal.

- The actual mechanism is not yet clear.  Current models (except maybe Kern and Stoop) do not adequately address the coupling issues.

- It is possible to model the system in dynamical systems terms (Hopf bifurcation) or conventional electronics and control terms (regenerative amplifiers & describing functions).  The two representations are equivalent.

- It is possible to build a conventional sonar system that uses this principle and achieves better SNR than a standard system.

# Event-based control systems

- Classical control theory
  - Discrete time (fixed sampling)
  - Discrete levels (quantization)
  - Works well in highly deterministic synchronous systems
- Event-based control systems
  - Continuous in time (irregular events)
  - Continuous or discrete in amplitude
  - Works well in asynchronous systems (neural, wireless control networks, …)

# Early days

- 1990

**A Neuron-based Pulse Servo for Motion Control**

Steve DeWeerth*, Lars Nielsen**, Carver Mead*, Karl Åström **

*Department of Computer Science, California Institute of Technology, Pasadena, Ca 91125, USA
**Department of Automatic Control, Lund Institute of Technology, Box 118, 221 00 Lund, Sweden

We see this technology as having applications in many areas. A very promising set of applications comes from biology itself. The control of artificial motor systems to mimic the behaviors of animals should be much more attainable if the low-level computational structures are also biologically related.

# Early days.......

classic event-based

- 2002

Proceedings of the 41st IEEE
Conference on Decision and Control
Las Vegas, Nevada USA, December 2002

WeP02-3

**Comparison of Riemann and Lebesgue Sampling for First Order Stochastic Systems**

**K. J. Åström**
Department of Mechanical & Environmental Engineering
University of California, Santa Barbara, CA 93 106
astrom@engineering.ucsb.edu

**B. M. Bernhardsson**
Ericsson Mobile Platforms
Nya Vattentornet, SE-221 83 Lund, Sweden
bo.bernhardsson@emp.ericsson.se

# Astrom ’02: His conclusions

The simple problems solved in this paper indicate that Lebesgue sampling may be worth while to pursue. The field of Lebesgue sampling is still in its infancy. There are many problems that may be worth while to pursue. The signal representation which is a mixture of analog and discrete is interesting, it is a good model for signals in biological systems. It would be very attractive to have a system theory similar to the one for periodic sampling. Particularly since many sensors that are commonly used today have this character. The design problem in the general case is still largely an unsolved problem. Implementation of controller of the type discussed in this paper can be made using programmable logic arrays without any need for AD and DA converters. There are many generalizations of the specific problems discussed in this paper that are worthy of further studies for example higher order systems and systems with output feedback.

# Early days……………….

- 2005 Varaiya Symposium, June 5, 2005 K. J. Åström

Little system theory is available!

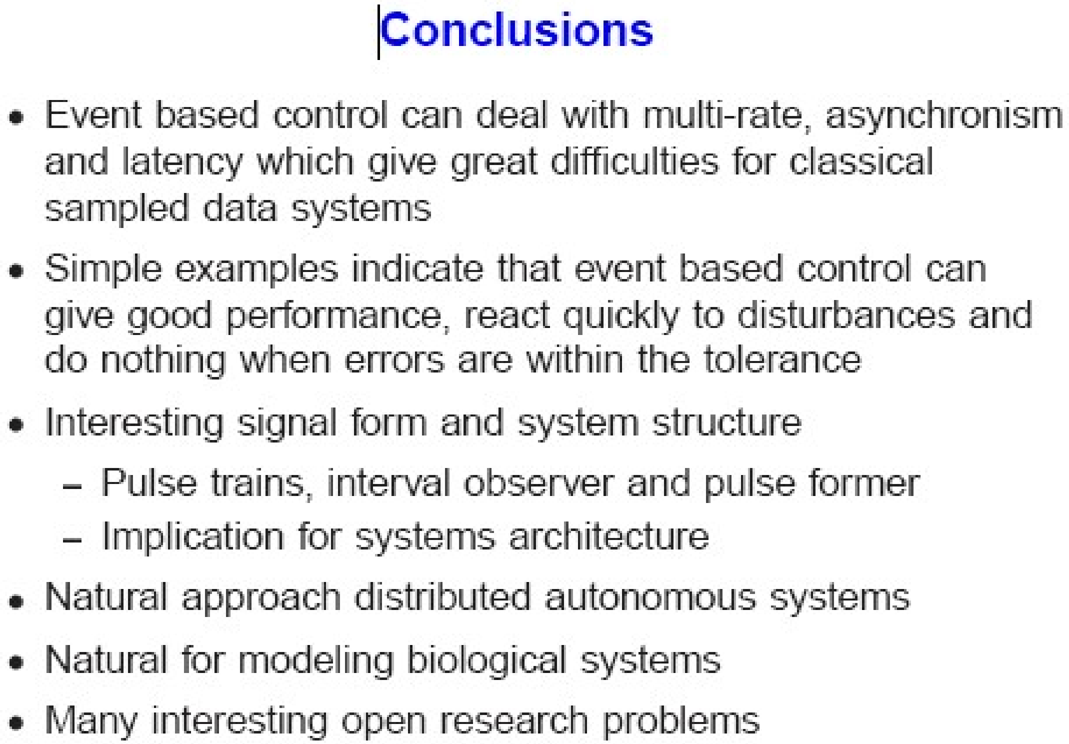
## Conclusions

- Event based control can deal with multi-rate, asynchronism and latency which give great difficulties for classical sampled data systems
- Simple examples indicate that event based control can give good performance, react quickly to disturbances and do nothing when errors are within the tolerance
- Interesting signal form and system structure
  - Pulse trains, interval observer and pulse former
  - Implication for systems architecture
- Natural approach distributed autonomous systems
- Natural for modeling biological systems
- Many interesting open research problems

Early days……………………….

- 2006 CASY Workshop Bertinoro, May 2006 K. J. Åström

**Traditional sample-data control requires 4.7 times faster sampling than event based control to give the same error variance!**



# Event-Based Control: Conclusions

- There has been limited progress (or interest) since 1990.
- As with most neuromorphic circuits, it is clear that asynchronous control offers considerable power saving potential, and possibly significantly better robustness to disturbance.
- Lack of a coherent mathematical structure is holding the field back from the point of classical control, but need not be an impediment to neuromorphic progress.

# Bibliography


- M.V. Srinivasan and G.D. Bernard, A proposed mechanism for multiplication of neural signals, Biol. Cybern. 21, 227-236, 1976.
- A. Borst and M. Egelhaaf, Principles of Visual Motion Detection, Trends. Neurosci., 1989 Aug;12(8):297-306.
- Gerstner, W., & Kistler, W. (2002). *Spiking Neuron Models: Single Neurons, Populations, Plasticity*, Cambridge University Press.
- Cariani, P.A., & Delgutte, B. (1996). Neural correlates of the pitch of complex tones I: Pitch and pitch salience, *J. Neurophysiol., 79*, 1698-1716.
- Colburn, H.S. (1996). For a review of cross-correlation models in auditory processing, see Colburn, H.S. (1996) “Binaural Models”, in *Springer Handbook of Auditory Research, Vol. 6: Auditory Computation*, Eds. H.L. Hawkin, T.A. McMullen, A.N. Popper, R.R. Fay, Springer, New York.
- Bulsara, A.R., Lowen, S.B., & Rees, C.D. (1994). Cooperative behavior in the periodically modulated Wiener process: Noise-induced complexity in a model neutron [sic]. *Phys. Rev. E, 49*, 4989-5000.
- J. Tapson and R. Etienne-Cummings, A Simple Neural Cross-Correlation Engine, Proc. IEEE Int. Symp. Circuits and Systems (ISCAS 2007), New Orleans, 1285-1288, 2007.
- O'Regan, J. Kevin and Noe, Alva (2001) A sensorimotor account of vision and visual consciousness. BEHAVIORAL AND BRAIN SCIENCES (2001) **24**(5)
- A neuron -based pulse servo for motion control, S. DeWeerth, L. Nielsen, K.J. Astrom, and C. Mead, 1991 – several sources.
- Comparison of Riemann and Lebesgue sampling for first order stochastic systems, K.J. Astrom and B. Bernardsson, Proc. 41st. IEEE Conf on Decision and Control, 2002.

# Acknowledgements

- University of Cape Town
  - John Greene
  - Mark Vismer

- Johns Hopkins University
  - Ralph Etienne-Cummings
  - Fopelofu Folowosele

- University of Sydney
  - Andre van Schaik
  - Tara Hamilton
  - Craig Jin

- And lots of other neuromorphs…many thanks.