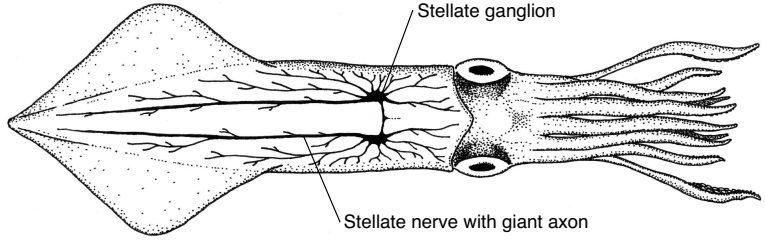
Risposta di neuroni singoli sottoposti a stimoli stocastici

S. Luccioli[2,3], T. Kreuz[1], & A. Torcini[1,2]

(1) Istituto dei Sistemi Complessi - CNR - Firenze

(2) INFN - Firenze

(3) Dipartimento di Sistemi e Informatica - Firenze



Collaborazioni in T061 a Firenze

Le linee di ricerca riconducibili a neuroscienze computazionali attualmente attive sono:

- Dinamica di reti neuronali, effetti del disordine e del ritardo
  - dr. Rüdiger Zillmer (Borsista – INFN)
  - prof. Roberto Livi (Dip. Fisica – INFN)
  - dr. Antonio Politi (Dir. Ricerca - ISC – CNR)
- Risposta di modelli di neurone sottoposti a stimoli stocastici
  - dr. Thomas Kreuz (European Marie-Curie Fellow - ISC – CNR)
  - Stefano Luccioli (Dottorando in Sistemi Complessi – INFN)

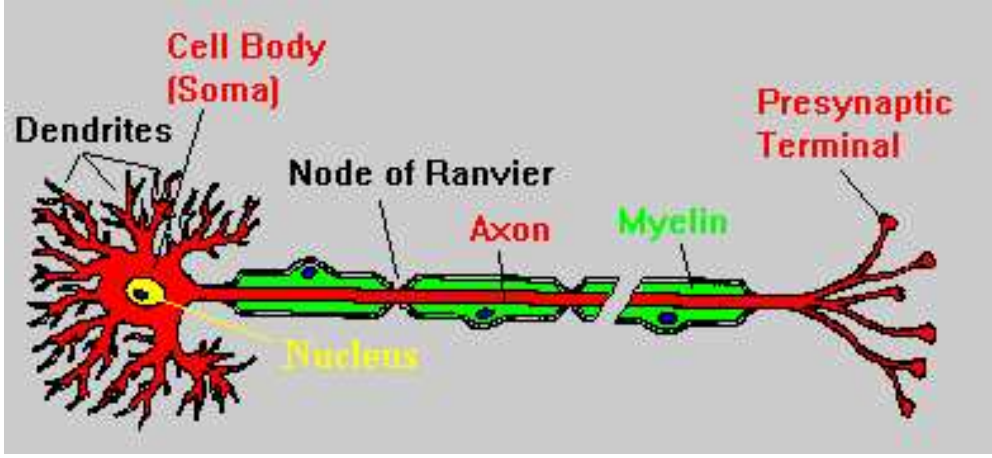
Tali studi sono principalmente computazionali, ma si avvalgono di concetti e metodologie proprie della meccanica statistica, della dinamica non-lineare, della teoria dell'informazione.

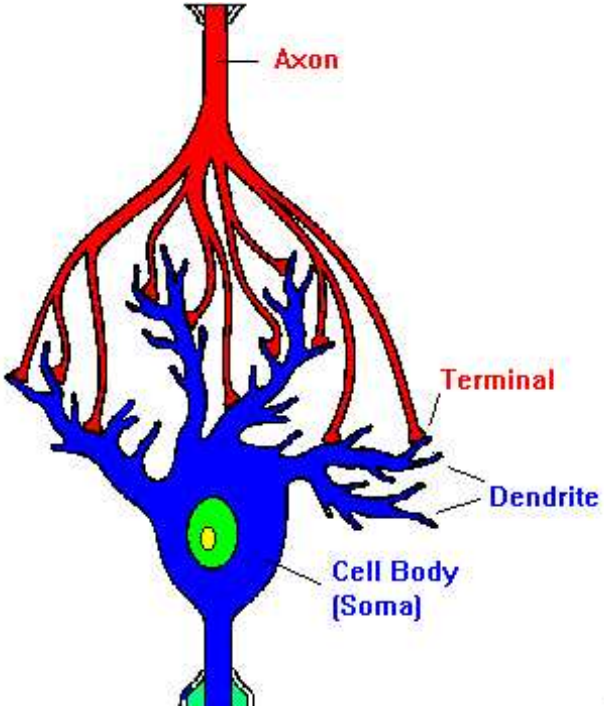
http://www.fi.isc.cnr.it/users/alessandro.torcini/neurores.html

Summary

- Introduction to the Hodgkin-Huxley model
- Characterization of the stochastic stimulation protocol
- Analysis of the neuronal responses for different noise levels
- Looking for coherence in the neuronal response
- Influence of correlations on the coherent response
- Conclusions

The neuron in brief

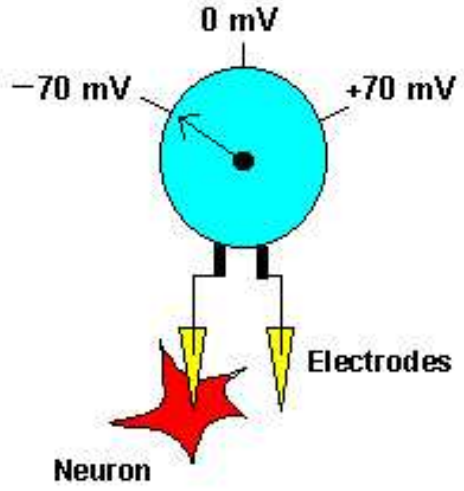


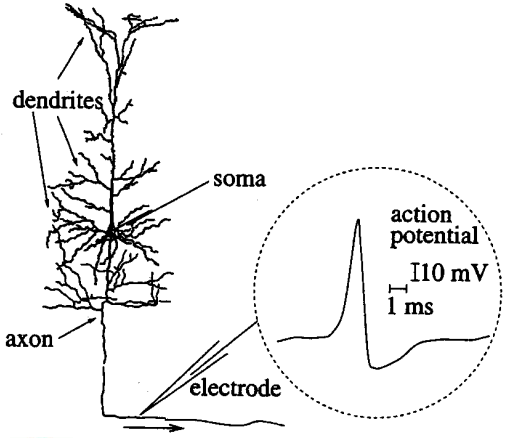


A neuron in the brain cortex has many ($\sim 5,000 - 60,000$) synaptic connections, but not all active. The neuron receives $300 - 1,000$ post-synaptic inputs of amplitude $\sim 0.5 - 1$ mV at a frequency ~ 100 Hz, it responds each $10 - 40$ inputs by emitting an action potential of duration $1 - 2$ msec and amplitude ~ 100 mV.

Segnali neuronali

Il potenziale di membrana V_m misura la differenza di potenziale fra interno ed esterno della cellula neuronale, nel neurone a riposo (non stimolato) $V_m \simeq$ -60mV / -75 mV
Il neurone é in equilibrio dinamico.





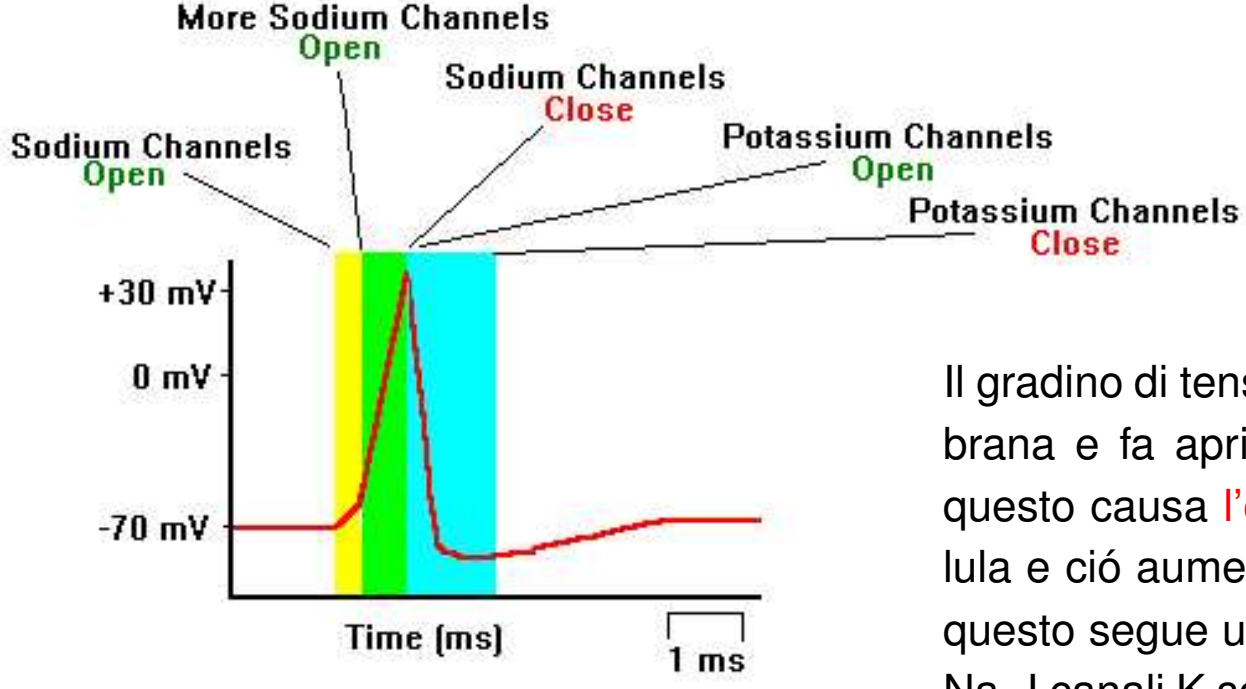
Il segnale neuronale indica la variazione temporale e spaziale di V_m. I potenziali di azione (PA) sono impulsi di tensione tipici generati durante la dinamica neuronale; essi hanno una forma pressoché stereotipata.

- Il PA é generato quando degli stimoli (depolarizzanti) portano V_m al di sopra di una soglia $\Theta \sim -55$ mV ;
- L'impulso ha durata di circa 1-2 ms ed una ampiezza di circa 100-120 mV ; nella fase di discesa l'impulso prima di ritornare al valore di riposo passa attraverso una fase di iperpolarizzazione, della durata di circa 10 ms . (fase di refrattarietá)
- Il PA, viaggia lungo l'assone ed è trasmesso (inalterato) agli altri neuroni, costituisce l'unità elementare associata alla trasmissione dei segnali neuronali.

Origine del potenziale d'azione

Inattivazione ed Attivazione dei Canali

Uno stimolo esterno fa alzare il potenziale di membrana dal suo valore di riposo $V_{rest} = -70$mV (DEPOLARIZZAZIONE) verso una soglia $\Theta = -55$ mV , allora si ha una escursione molto ampia del potenziale di membrana: un PA o uno SPIKE



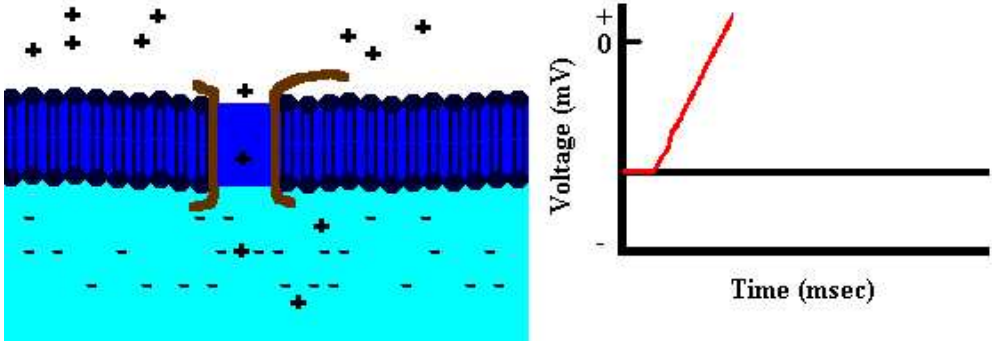
$[Na^+]_e >> [Na^+]_i$ $[K^+]_e << [K^+]_i$

Il gradino di tensione depolarizza la membrana e fa aprire i canali Na (li attiva), questo causa l'entrata del Na^+ nella cellula e ció aumenta la depolarizzazione, a questo segue una inattivazione dei canali Na. I canali K sono attivati con un certo ritardo e questo causa la fuoriuscita del K^+ e la ripolarizzazione della membrana.

Origine del potenziale d'azione

Depolarizzazione e ripolarizzazione della membrana

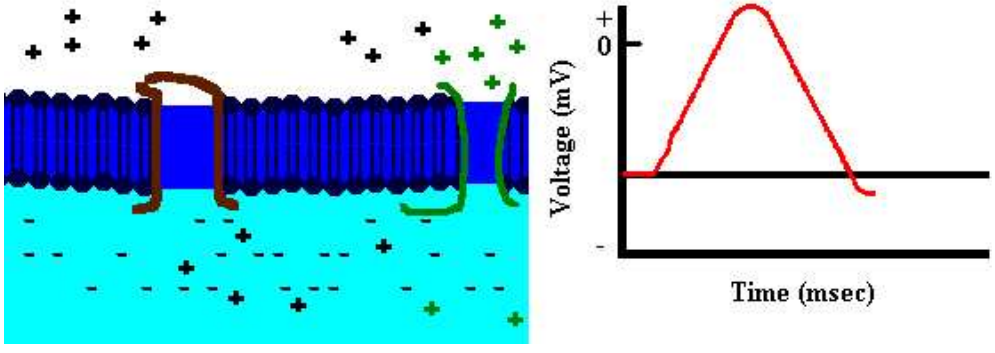
Depolarizzazione della membrana



Na^+ entra nella cellula

$V_m \rightarrow E_{Na+} = +55$ **mV**

Ripolarizzazione della membrana



K^+ lascia la cellula

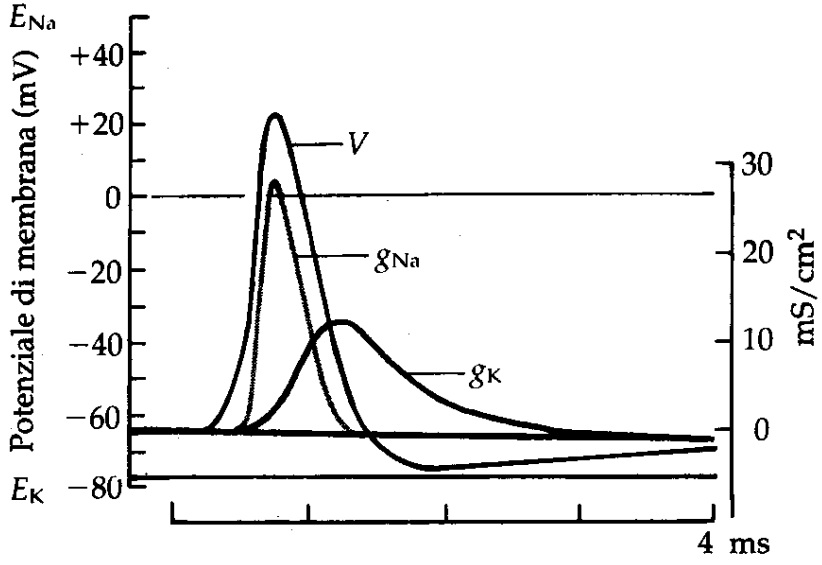
$V_m \rightarrow E_{K+} = -75$ **mV**

Origine del potenziale d'azione

Correnti in gioco e conduttanze

Le correnti in gioco nella generazione del potenziale di azione sono per l'assone gigante del Calamaro solamente tre:

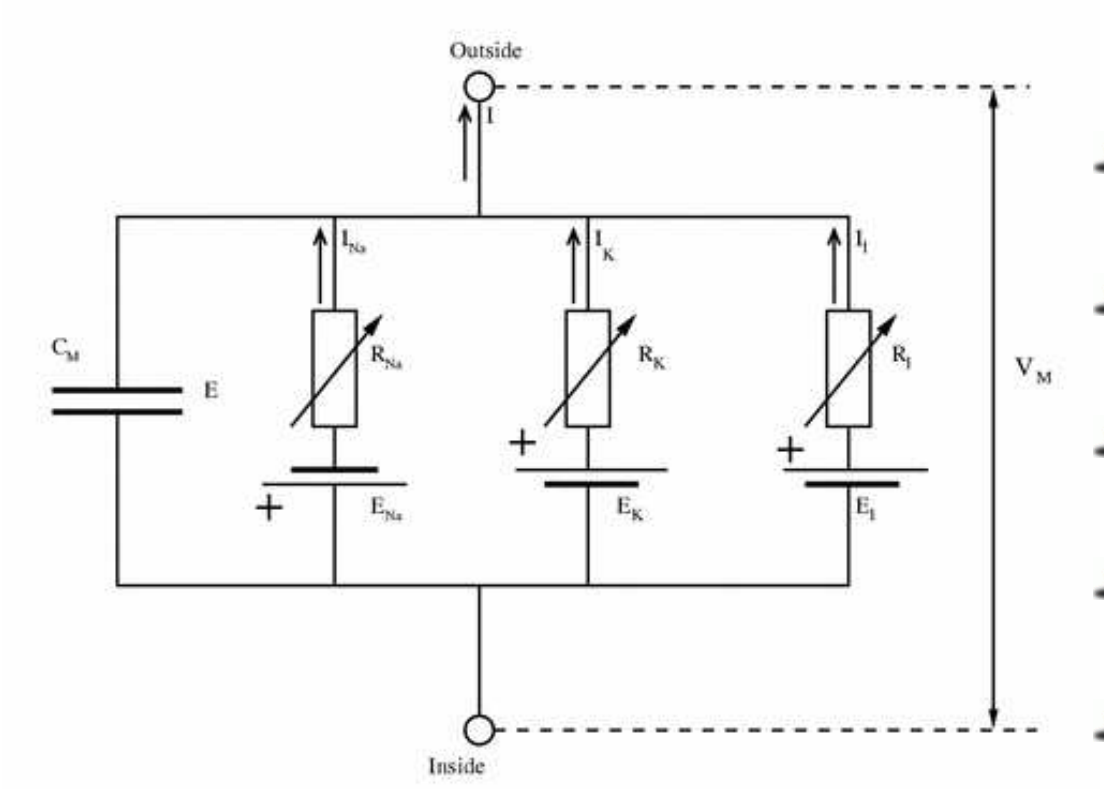
- la corrente del sodio $I_{Na} = g_{Na}(V - E_{Na})$ —- $g_{Na} = \frac{1}{R_{Na}} = g_{Na}(V)$
- la corrente del potassio $I_K = g_K(V - E_K)$ —- $g_K = \frac{1}{R_K} = g_K(V)$
- la corrente di perdita (leakage) $I_L = g_L(V - E_L)$ é dovuta principalmente allo ione Cl^-, ma riassume l'effetto anche di altre correnti ioniche minori



L'apertura (chiusura) dei canali Na e K dipende dal valore del potenziale di membrana, le conduttanze del Na e K dipendono da V , le correnti del Na e K dipendono nonlinearmente da V.

Origine del potenziale d'azione

Schema circuitale della membrana



- Schema per un pezzetto di membrana
- Legge dei Nodi
  $I(t) = I_C + I_{Na} + I_K + I_L$
- corrente capacitiva
  $I_C = dQ/dt = CdV/dt$
- correnti ioniche I_{Na} e I_K (nonlineari)
- corrente di perdita (lineare)

$$C\frac{dV}{dt} = -I_{Na} - I_K - I_L + I_{syn}(t)$$

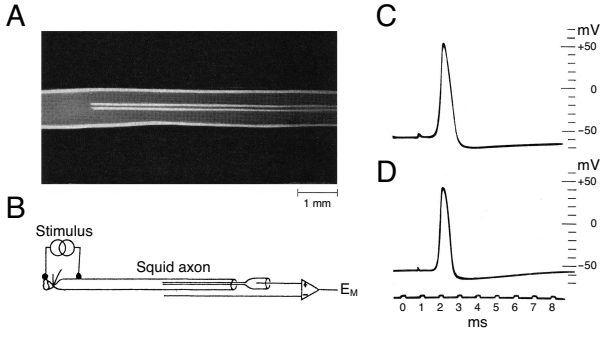
Il problema é calcolare sperimentalmente come variano le conduttanze g_{Na} e g_K al variare del potenziale di membrana, la loro dinamica.

The Hodgkin-Huxley model

Hodgkin

The HH model reproduces the time evolution of the membrane potential and of the ionic currents measured experimentally for a giant squid axon.

Huxley



$C = 1\mu F/cm^2$ - Membrane capacitance

V - Membrane Potential (mV)

I_j - Ionic channel currents $(\mu A/cm^2)$

$\bar{g}_j$ - Maximal ionic conductances (mS/cm^2)

V_j - Ionic reversal potentials (mV)

$$C\dot{V} = \sum_j I_j + I_{syn} = -\bar{g}_{Na} m^3 h (V - V_{Na}) - \bar{g}_K n^4 (V - V_K) - g_L (V - V_L) + I_{syn}$$

$$\dot{x} = \alpha_x - x(\alpha_x + \beta_x) \qquad x = n, m, h \qquad \text{gating variables}$$

$\alpha_x = \alpha_x(V)$ and $\beta_x = \beta_x(V)$ are highly nonlinear functions.

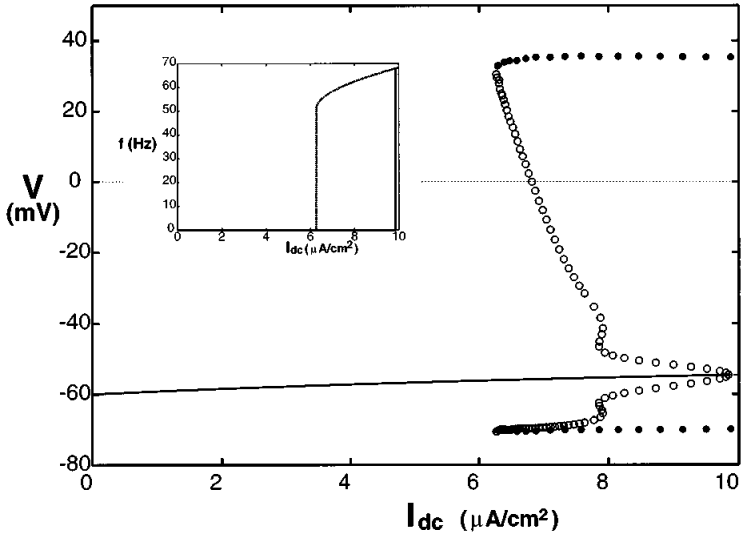
The Hodgkin-Huxley model

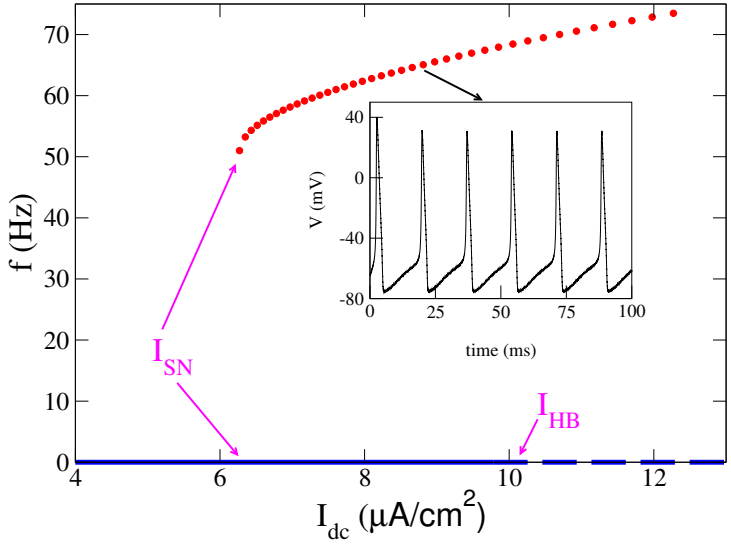
Hodgkin

The HH model reproduces the time evolution of the membrane potential and of the ionic currents measured experimentally for a giant squid axon.

Huxley

Constant Current Synaptic Input $I_{syn} = I_{dc}$





Main motivations

- A neuron in the brain cortex is subject to a continuous synaptic bombardament of inputs, resembling a background noise
  (A. Destexhe, M. Rudolph, D. Paré - Nature Reviews - Neuroscience - 2003)
- Inputs are mainly originating from the cortex itself, their statistical properties of can be (roughly) summarized as
  - Frequency range $100 - 200$ Hz;
  - Amplitude $\sim 0.5 - 1$ mV;
  - Distribution of the arrival times : approximately Poissonian (exponential).

  (M.N. Shadlen & W.T. Newsome, J. Neuroscience - 1998)
- Neurons in the cortex, due to the high connectivity, can receive inputs from the same axon: correlation via common drive;
  - Correlations in the inputs can influence the firing rate of the neuron;
  - Correlations can regulate the flow of neural information: attention, etc;

  (E. Salinas & T.J. Sejnowski, J. Neuroscience - 2000; Nature Rev. Neurosci. - 2001)

How can a neuron driven by noise emit some sort of regular (coherent) signal ?

How do correlated stochastic inputs influence the response of single neurons ?

High-input regime

- Instead of a constant current I_{dc}, we consider N_E excitatory (EPSP) and N_I inhibitory postsynaptic inputs (IPSP), each corresponding to a voltage kick $\Delta V_0 = 0.5$ mV.

High-input regime

- Instead of a constant current I_{dc}, we consider N_E excitatory (EPSP) and N_I inhibitory postsynaptic inputs (IPSP), each corresponding to a voltage kick $\Delta V_0 = 0.5$ mV.
- These inputs originate from neurons emitting Poissonian spike trains with frequency $\nu = 100$ Hz.

High-input regime

- Instead of a constant current I_{dc}, we consider N_E excitatory (EPSP) and N_I inhibitory postsynaptic inputs (IPSP), each corresponding to a voltage kick $\Delta V_0 = 0.5$ mV.
- These inputs originate from neurons emitting Poissonian spike trains with frequency $\nu = 100$ Hz.
- This amounts to one excitatory (resp. inhibitory) Poissonian spike train with frequency $\nu_E = N_e \times \nu \sim 10^4 - 10^5$ Hz (resp. $\nu_I = N_I \times \nu$) for $N_e \sim N_I \sim 100 - 1,000$.

High-input regime

- Instead of a constant current I_{dc}, we consider N_E excitatory (EPSP) and N_I inhibitory postsynaptic inputs (IPSP), each corresponding to a voltage kick $\Delta V_0 = 0.5$ mV.
- These inputs originate from neurons emitting Poissonian spike trains with frequency $\nu = 100$ Hz.
- This amounts to one excitatory (resp. inhibitory) Poissonian spike train with frequency $\nu_E = N_e \times \nu \sim 10^4 - 10^5$ Hz (resp. $\nu_I = N_I \times \nu$) for $N_e \sim N_I \sim 100 - 1,000$.
- Firstly independent inputs are considered , and then also the effect of correlations among the inputs is analyzed.

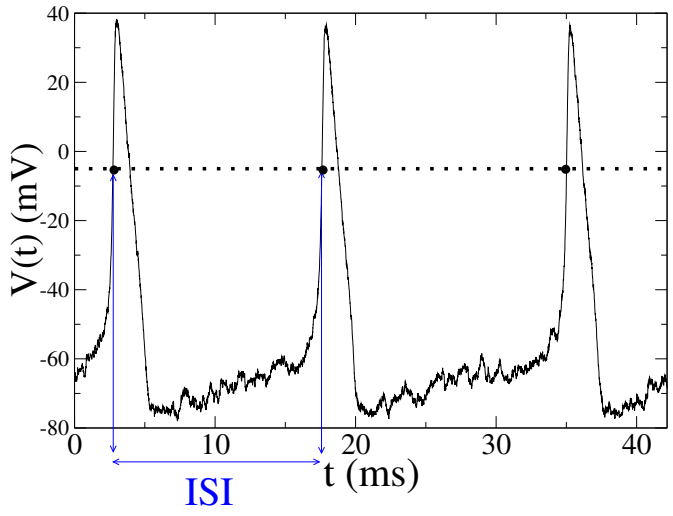
High-input regime

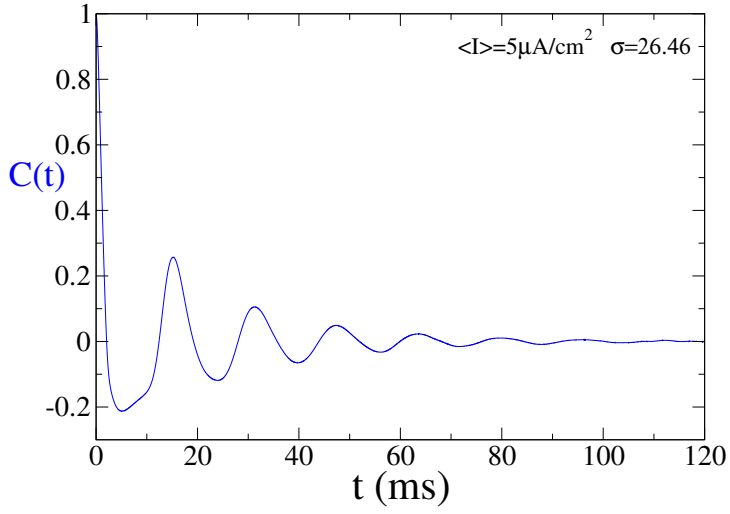
- Instead of a constant current I_{dc}, we consider N_E excitatory (EPSP) and N_I inhibitory postsynaptic inputs (IPSP), each corresponding to a voltage kick $\Delta V_0 = 0.5$ mV.
- These inputs originate from neurons emitting Poissonian spike trains with frequency $\nu = 100$ Hz.
- This amounts to one excitatory (resp. inhibitory) Poissonian spike train with frequency $\nu_E = N_e \times \nu \sim 10^4 - 10^5$ Hz (resp. $\nu_I = N_I \times \nu$) for $N_e \sim N_I \sim 100 - 1,000$.
- Firstly independent inputs are considered , and then also the effect of correlations among the inputs is analyzed.

At these frequencies the net input spike count within a temporal window ΔT (≥ 1 msec) is essentially Gaussian distributed and it can be characterized by its average $\mu = \nu(N_E - N_I)\Delta T$ and variance $V = \nu(N_E + N_I)\Delta T = \nu\sigma^2\Delta T$.

The response of the neuron is examined for fixed average input current $\bar{I} = C\Delta V_0 \nu(N_E - N_I)$ by varying only σ and therefore the standard deviation of the noise.

Statistical and dynamical indicators

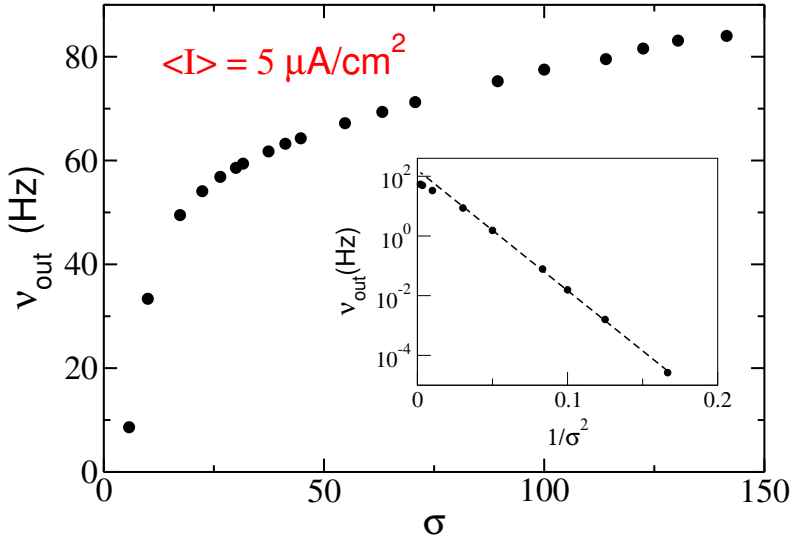


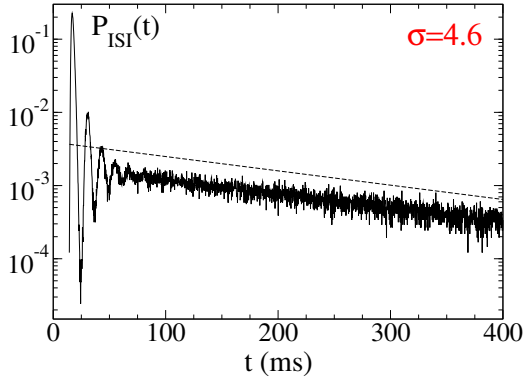


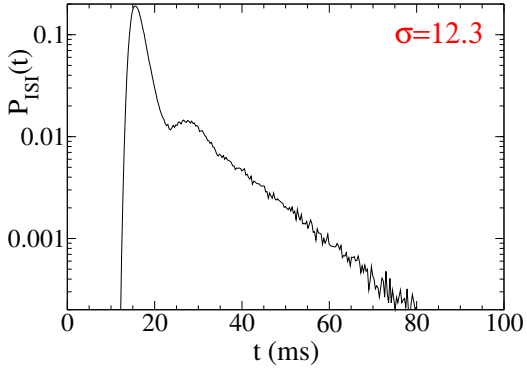
- ISI distribution $\longrightarrow P_{ISI}(t)$;
- $CV = \frac{Std(ISI)}{\langle ISI \rangle}$ $\longrightarrow$ coefficient of variation of the ISIs:
  Poisson distribution $\longrightarrow CV = 1$ *** regular sequence $\longrightarrow CV = 0$;
- $\tau_c = \int_0^\infty C^2(t)dt \longrightarrow$ correlation time, $C(\tau) = \frac{\langle V(t+\tau)V(t)\rangle - \langle V\rangle^2}{\langle V^2\rangle - \langle V\rangle^2}$
- Conditional entropies (not discussed here)

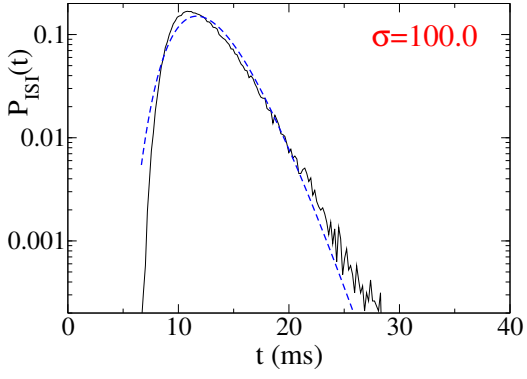
Response of the silent neuron

The HH neuron is in the silent state, i.e. the average input current $\bar{I}$ is smaller than I_{SN}.



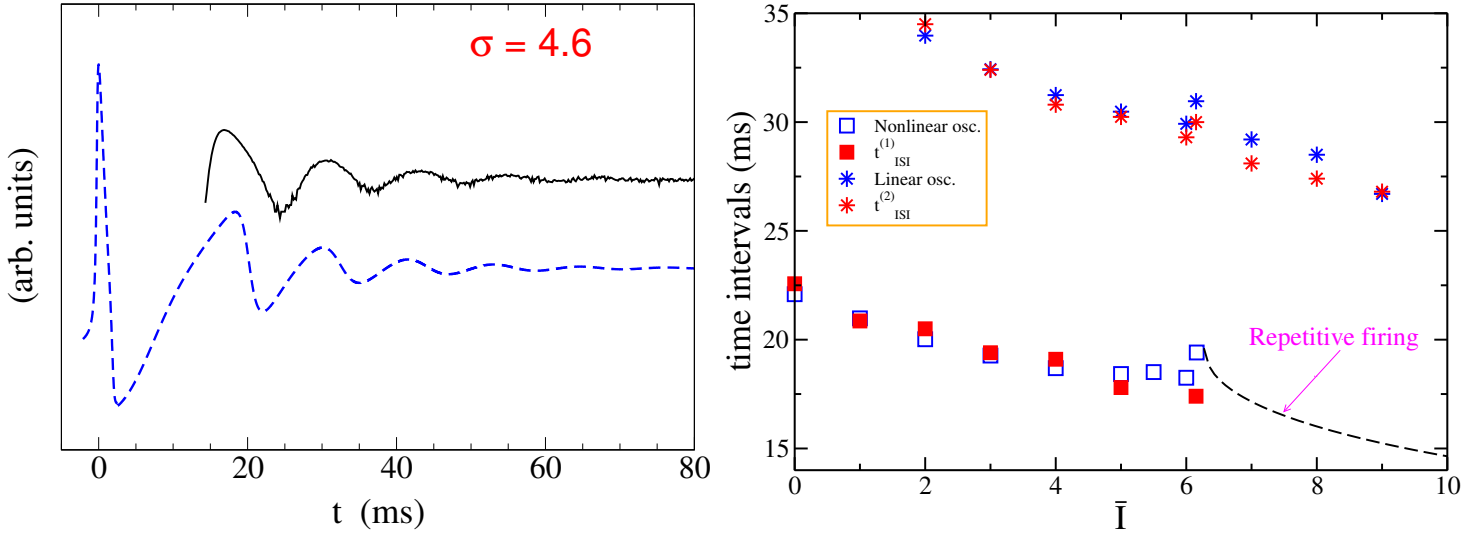






Response of the silent neuron

Spikes triggered by relaxation oscillations



The neuronal spiking is enhanced in correspondence of the maxima of the relaxation oscillations following a spike emission.

The first oscillation has a nonlinear origin, while the period of the subsequent ones can be obtained via a linear analysis around the stable fixed point solution (focus).

Response of the silent neuron

Firing activated by noise

Two mechanisms compete:

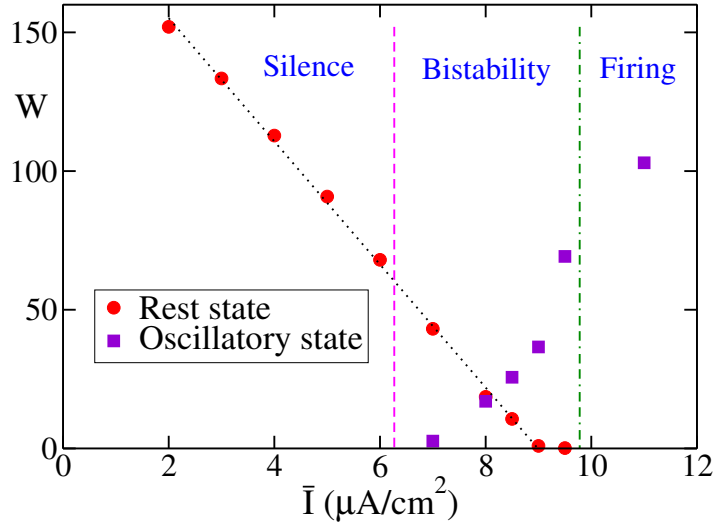
- the HH dynamics tends to relax towards the rest state;
- noise fluctuations lead the system towards an excitation threshold.

The dynamics of $V(t)$ resembles the overdamped dynamics of a particle in a potential well under the influence of thermal fluctuations, and the firing times can be expressed in terms of the Kramers expression (for sufficiently small noise)

$$t_a \propto \mathrm{e}^{W_S/\sigma^2}$$

the time distribution is Poissonian ($CV = 1$).

- for $\sigma < \sqrt{W_S}$ $\longrightarrow$ Activation Process
- for $\sigma > \sqrt{W_S}$ $\longrightarrow$ Diffusive Dynamics



Response of the silent neuron

High noise limit

The effect of noise fluctuations on the neuron dynamics is twofold:

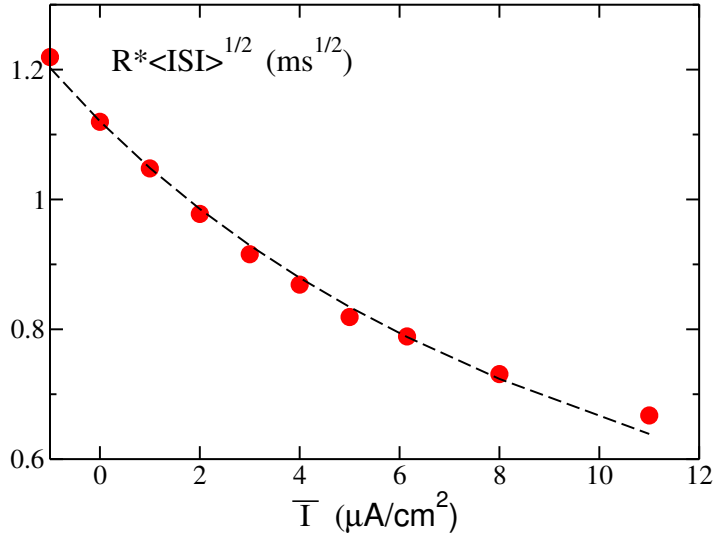
- a constant current $\bar{I}$ driving the system;
- a stochastic term with zero average.

The dynamics of $V(t)$ can therefore be described in terms of a Langevin process with a drift and the distribution of the first passage times is given by the inverse Gaussian distribution:

$$f(t) = \frac{\alpha}{\sqrt{2\pi\beta t^3}} \mathrm{e}^{-\frac{(t-\alpha)^2}{2\beta t}}$$

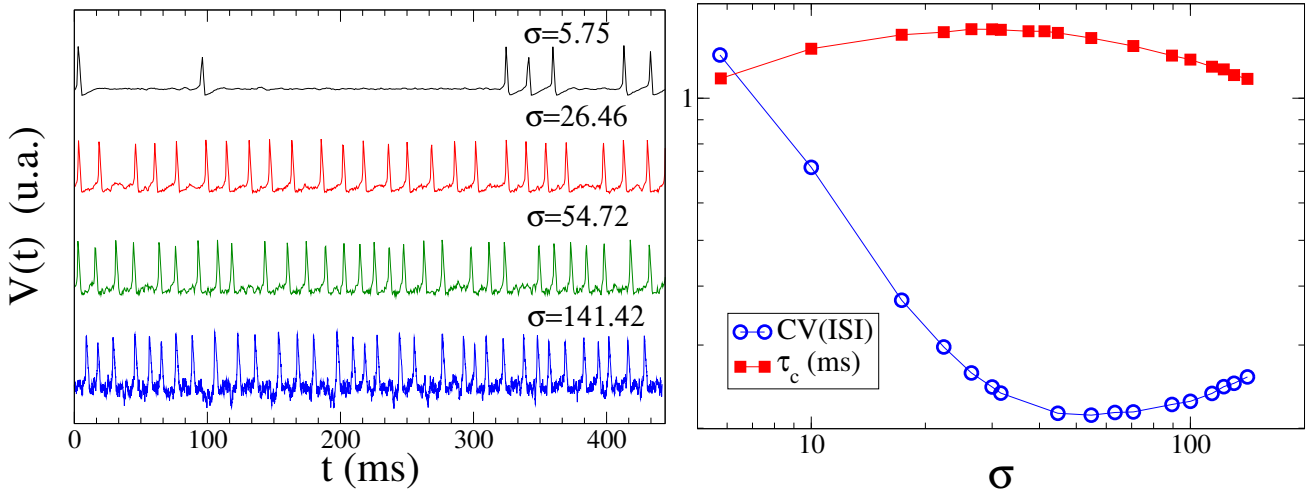
In this case the coefficient of variation should be given by

$$CV \propto \frac{\sigma}{(\bar{I} + I_0)\sqrt{< ISI >}}$$



Coherence resonance

Coherence of the emitted spike trains

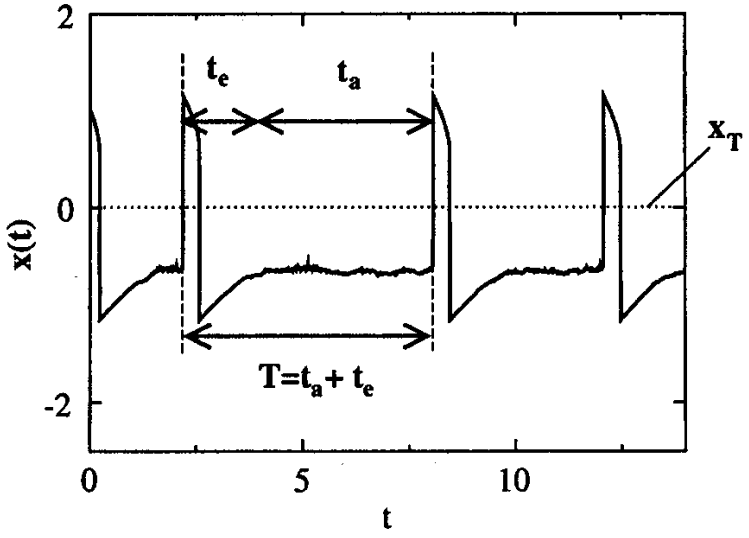


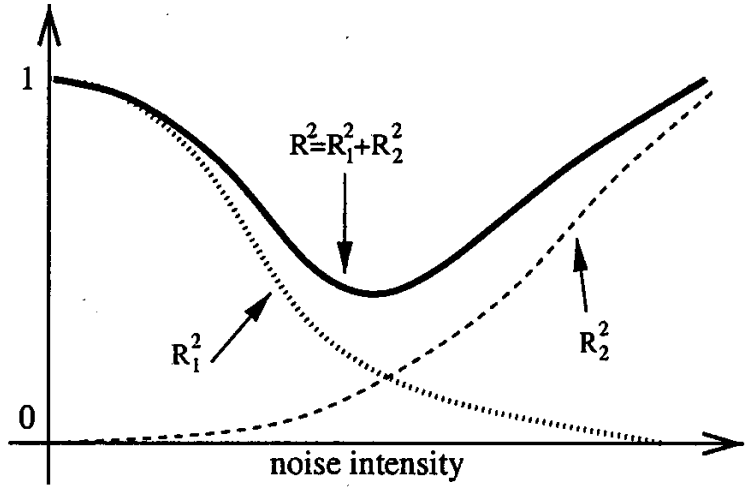
In the silent and bistable regime ($I < 8\mu$A/cm^2):

- by increasing σ the firing rate increases, the spike train becomes more regular (Activation Process);
- the maximal coherence is reached for a optimal σ-value;
- for higher noise amplitudes the noise influence even the duration of the single spike, the response becomes again more irregular (Brownian motion + drift).

A. Pikovsky & J. Kurths, PRL 78, 775 (1997)

Coherence resonance





- The system is characterized by two characteristic times $\longrightarrow ISI \equiv T = t_a + t_e$:
  - t_a=activation time $\longrightarrow$ time needed to excite the system;
  - t_e=excursion time $\longrightarrow$ duration of the spike (excited state).
- $CV(T)$ can be splitted in two contributions

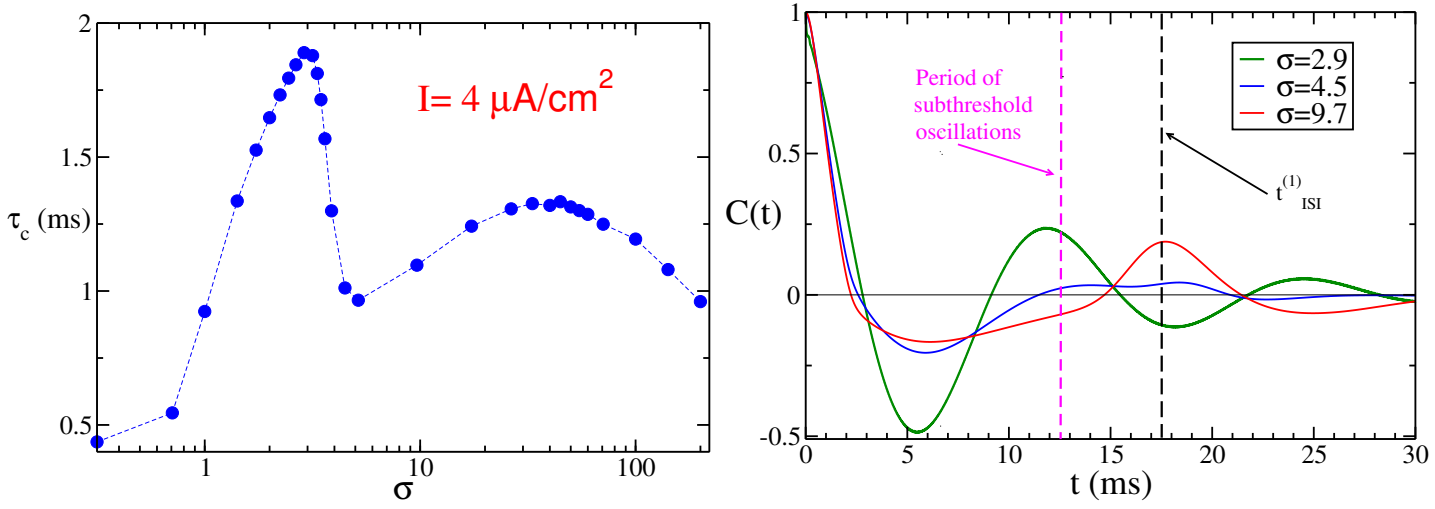
$$CV(T)^2 = CV(t_a)^2 \frac{<t_a>^2}{<T>^2} + CV(t_e)^2 \frac{<t_e>^2}{<T>^2} = R_1^2(t_a) + R_2^2(t_e)$$

$R_1^2(t_a)$ decreases with σ, while $R_2^2(t_e)$ increases $\longrightarrow$ minimum in $CV(T)$

B. Lindner *et al.*, Phys Rep. 392 (2004) 321-424

Coherence resonance

Coherence of the subthreshold oscillations



A second coherence resonance is revealed by analyzing the correlations of the potential:

- for $\sigma < 3$ almost no spikes are emitted, but the increase of noise leads to more and more regular subthreshold oscillations;
- for $\sigma > 3$ the statistics of the emitted spikes is no more negligible and this decorrelates the signal;
- for $\sigma > 10$ the dynamics is dominated by sequences of spikes and a second peak occurs related to the regularization of the spike trains.

S. Luccioli. T. Kreuz, A.T. Phys. Rev. E (2006)

Correlations via common drive

The correlation between two input spike trains originating from neuron i and j is measured in terms of the Pearson correlation coefficient :

$$\rho = \frac{< (n_i - \langle n_i \rangle)(n_j - \langle n_j \rangle) >}{s^2}$$

where n is the number of input spikes in a time window ΔT and s^2 its variance.

Correlations among either excitatory or inhibitory inputs are considered in the balanced case $N_E = N_I \equiv N$ ($< I > \equiv 0$).

M.N. Shadlen & W.T. Newsome (1998) – E. Salinas & J. Sejnowski (2000)

Correlations via common drive

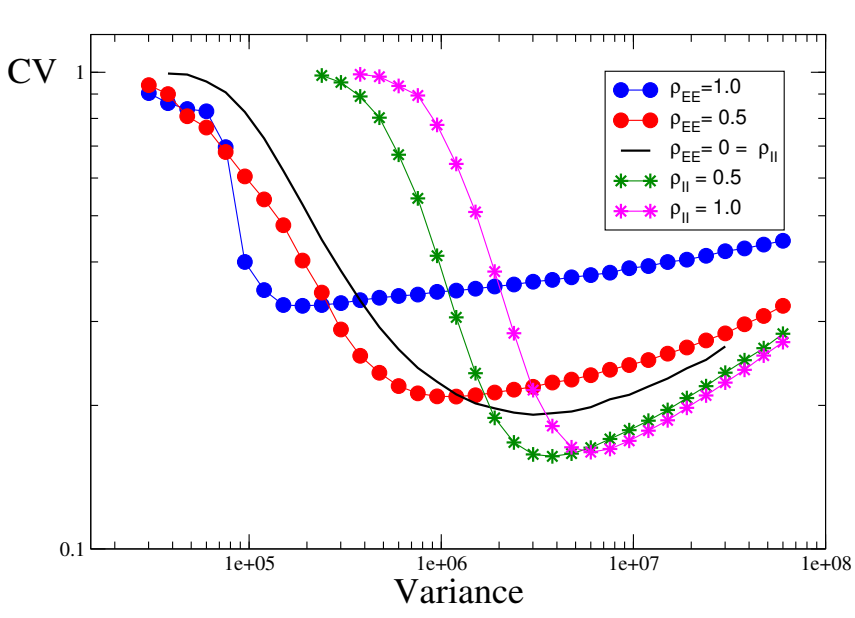
- The superposition of N correlated (ρ) Poissonian spike trains with rate ν_0 gives rise to a sequence of kicks of variable amplitude (binomially distributed) and with ISIs Poissonian distributed with rate ν_0/ρ;
- For correlated kicks: average amplitude $< \Delta V >= \rho N \Delta V_0$ and average frequency $\nu_c = \nu_0/\rho$;
- For uncorrelated kicks: frequency=$N\nu_0$ and constant amplitude= ΔV_0.
- The noise variance is influenced by correlations $\sigma \sim < \delta V >^2 \times \nu_c$ while $< I > \equiv 0$ not.

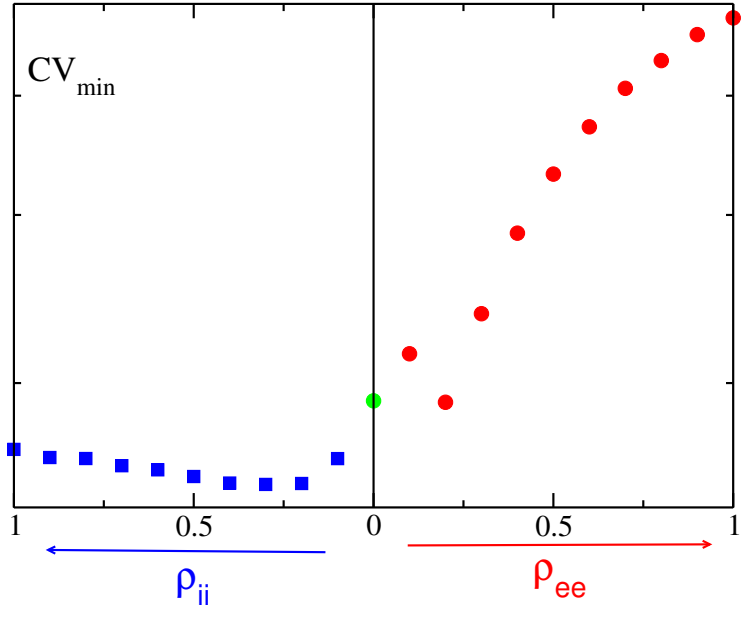
The uncorrelated spike trains can be assimilated to an almost continuous background that renormalizes the input current, while the correlated kicks can be seen as rare events of large amplitude.

Response to correlated inputs

We have studied the response of the (balanced $N_E = N_I$) model in the silent regime for excitatory (resp. inhibitory) correlated inputs at constant correlation ρ by varying the noise variance.

- Coherence Resonance (CR) is observed for any excitatory (resp. inhibitory) correlation at finite noise amplitude.
- An absolute CR with respect to noise and correlation can be identified.





Response to correlated inputs

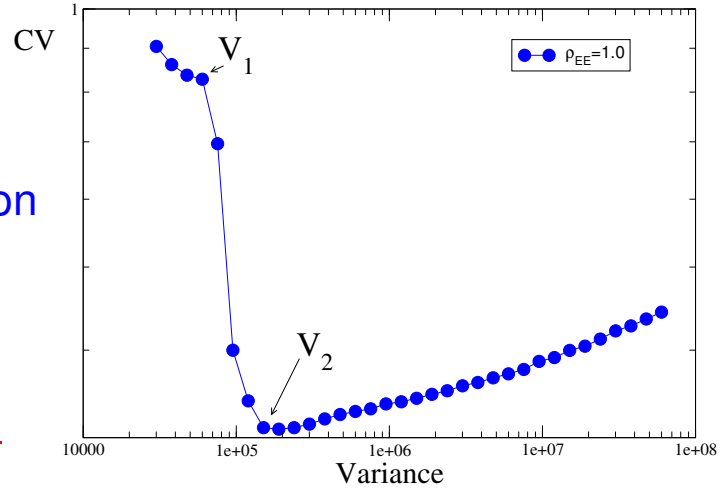
Strong excitatory correlation

The coherence phenomenon is now determined only by the kick amplitude and not by the properties of the asymptotic stochastic processes, since in the present case the output can be always described as a Poissonian process with a refractory time.

For increasing variance (i.e. increasinh N) the amplitude of the correlated kicks increases.

- for $Variance < V_1 \longrightarrow$ Activation Process
- for $V_1 < Variance < V_2$
  1 kick may be sufficient to induce a spike emission
- for $V_2 < Variance$
  One kick elicits always a spike - T_{ref} decreases

$$CV = \frac{T}{T + T_{ref}}$$



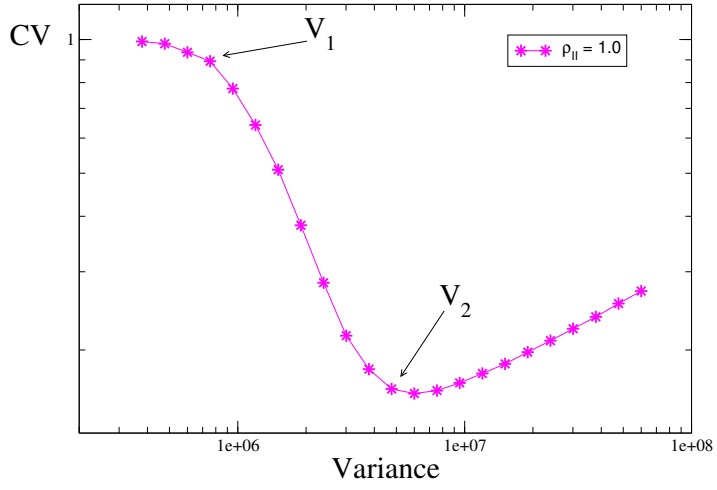
For $Variance > V_2 \rightarrow T = 1/\nu_0$, we have a $1:1$ synchronization between input and output (apart from the refractory period).

Response to correlated inputs

Strong inhibitory correlation

At large variances the dynamics is again ruled by the the amplitude of the correlated kicks, but at lower variances the inhibitory kicks are quite infrequent and their amplitude is not sufficient to influence the dynamics.

- for $Variance < V_1$
  Silent regime - Activation Process - $CV \simeq 1$
- for $V_1 < Variance < V_2$
  Dynamics dominated by uncorrelated excitatory input leading the system in the repetitive firing regime
- for $Variance > V_2$
  Each inhibitory kick induces a certain delay in the spike time of the neuron - A multimodal structure appears in the ISI distribution



Frequency of the correlated kicks (ν_0) $<<$ Frequency of the uncorrelated kicks ($N\nu_0$)

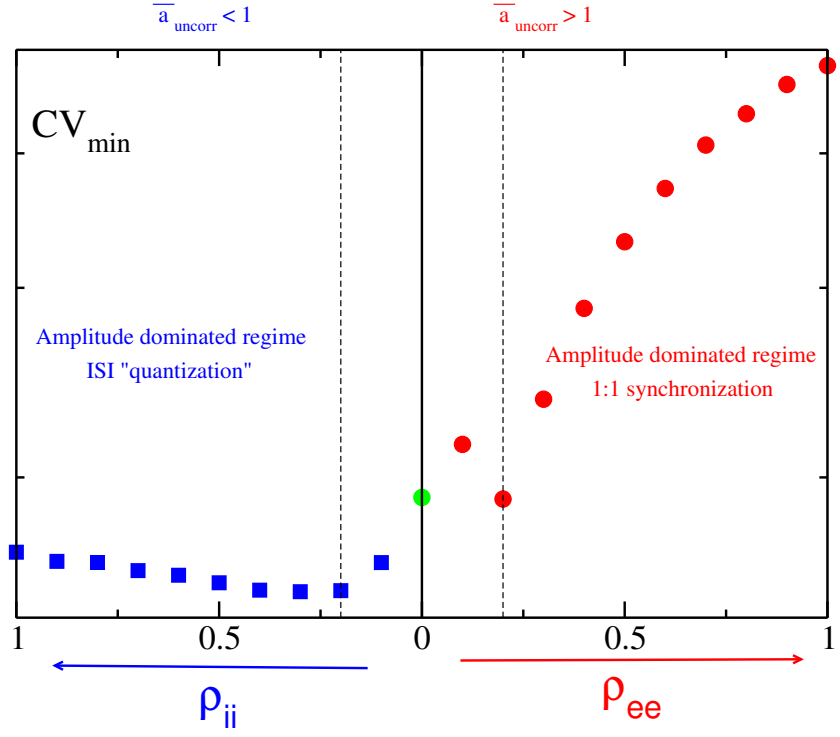
Response to correlated inputs

Maximal Coherence

Absolute minima of CV corresponding to maximal coherence are observed at finite noise and correlation for both inhibitory and excitatory case.

The extrema of CV_{min} indicate the change in the mechanisms inducing CR, from amplitude dominated to usual mechanisms related to the crossover from activated to (biased) diffusive processes.

The CV_{min} associated to inhibitory correlations are lower since the system is driven in the repetitive firing regime by the uncorrelated input.

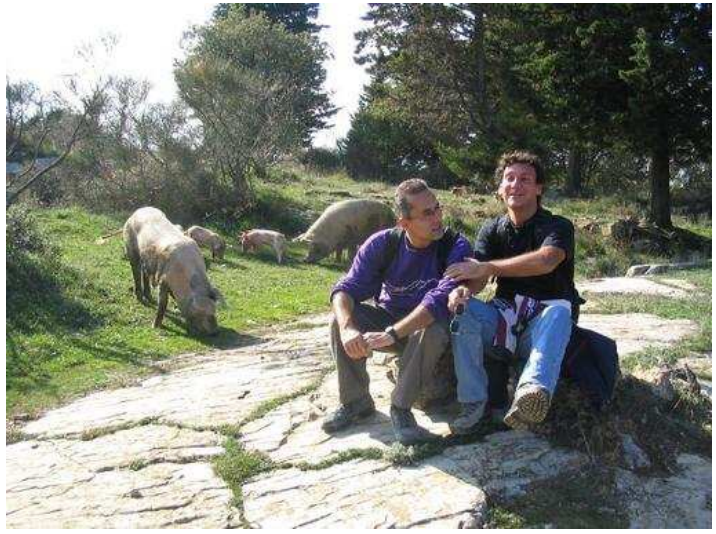


Conclusions

- Uncorrelated stochastic inputs
  - The neuronal firing, induced by the stochastic inputs, can be interpreted as an activation process at low variances (σ), while for large σ this process becomes essentially diffusive;
  - at low noise, beside of the exponential tail, the ISI distributions reveal a multimodal structure due to spiking triggered by relaxation oscillations towards the rest state;
  - coherence resonance can be observed in a large interval of currents in the silent and bistable regime whenever $W_S > W_O$;
  - a second coherence resonance (associated to subthreshold oscillations) coexists with the usual one;
- Correlated stochastic inputs
  - new mechanisms for the coherence resonance have been reported at high excitatory and inhibitory correlations;
  - maximal coherence can be induced by an optimal combination of noise and correlation

Credits

- Stefano Luccioli - MSc in Physics (2004-2005)
- Dynamics of realistic single neuronal models

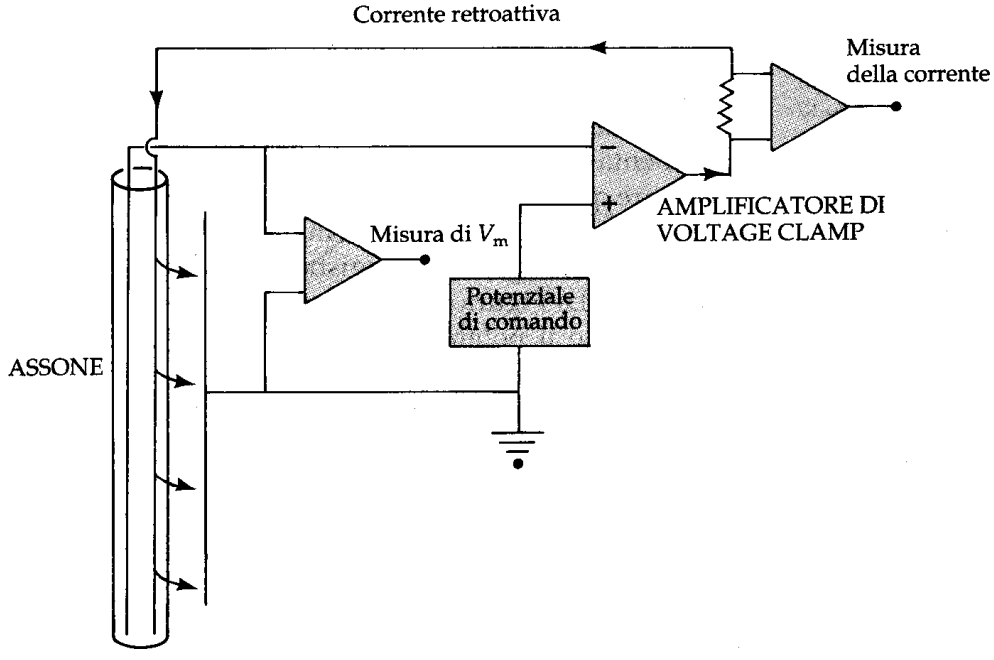


- Thomas Kreuz - Marie Curie Fellow (2005-2006)
- Dynamical Entropies in Assemblies of Neurons

http://www.fi.isc.cnr.it/users/alessandro.torcini/neurores.html

L'esperimento di Voltage-Clamp

L'esperimento di blocco del voltaggio (voltage clamp) consiste nell'inserire nell'assone del calamaro due elettrodi (fili di argento), uno che serve a misurare V_m e l'altro per trametterе corrente dentro l'assone cosí da mantenere (retroattivamente) V_m costante.



Effetti positivi del voltage clamp:

- elimina la corrente capacitiva $I_C \equiv 0$;
- si possono misurare le dipendenze temporali delle varie correnti (conduttanze) a V_m costante;
- inserendo gli elettrodi si ha anche uno space-clamp cioé tutta la lunghezza dello assone ha lo stesso V_m

HH were able to measure separately the different currents thanks to pharmacological products able to block selectively the different ionic channels.

The FitzHugh-Nagumo Model

The FitzHugh-Nagumo (FHN) model is a two dimensional *"simplification"* of the HH model:

$$\dot{V} = \phi(V - \frac{V^3}{3} - W) \quad ;$$

$$\dot{W} = V + a - I(t)$$

where V is a voltage-like variable, W is a recovery variable and a is the bifurcation parameter.

For $\phi = 100$ the silent regime is observed for $a < 1$, while at $a > 1$ one has periodic firing.

$$I(t) = \Delta W_0 \left[\sum_{k=1}^{N_e} \sum_{l} \delta(t - t_k^l) - \sum_{m=1}^{N_i} \sum_{n} \delta(t - t_m^n) \right]$$

We examine the FHN model subject to N_E (resp. N_I) trains of excitatory (resp. inhibitory) post-synaptic potentials, in the balanced case (i.e. for $N_E = N_I \equiv N$) where $< I > \equiv 0$ for $a = 1.05$ and $\Delta W_0 = 0.0014$.

Correlations via common drive

- Correlations only among excitatory or inhibitory inputs are considered in the balanced case $N_E = N_I \equiv N$;

Correlations via common drive

- Correlations only among excitatory or inhibitory inputs are considered in the balanced case $N_E = N_I \equiv N$;
- The superposition of N correlated (ρ) Poissonian spike trains with rate ν_0 gives rise to a sequence of kicks of variable amplitude (binomially distributed) and with ISIs Poissonian distributed with rate ν_0/ρ;

Correlations via common drive

- Correlations only among excitatory or inhibitory inputs are considered in the balanced case $N_E = N_I \equiv N$;
- The superposition of N correlated (ρ) Poissonian spike trains with rate ν_0 gives rise to a sequence of kicks of variable amplitude (binomially distributed) and with ISIs Poissonian distributed with rate ν_0/ρ;
- The average input is not influenced by correlations $< I > \equiv 0$, instead the noise variance is $\Delta V^2 \nu_0 [N^2 \rho + N(1-\rho) + N]$;

Correlations via common drive

- Correlations only among excitatory or inhibitory inputs are considered in the balanced case $N_E = N_I \equiv N$;
- The superposition of N correlated (ρ) Poissonian spike trains with rate ν_0 gives rise to a sequence of kicks of variable amplitude (binomially distributed) and with ISIs Poissonian distributed with rate ν_0/ρ;
- The average input is not influenced by correlations $< I > \equiv 0$, instead the noise variance is $\Delta V^2 \nu_0 [N^2 \rho + N(1-\rho) + N]$;
- For correlated kicks: average amplitude=$\rho N \Delta V$ and average frequency=ν_0/ρ;

Correlations via common drive

- Correlations only among excitatory or inhibitory inputs are considered in the balanced case $N_E = N_I \equiv N$;
- The superposition of N correlated (ρ) Poissonian spike trains with rate ν_0 gives rise to a sequence of kicks of variable amplitude (binomially distributed) and with ISIs Poissonian distributed with rate ν_0/ρ;
- The average input is not influenced by correlations $< I > \equiv 0$, instead the noise variance is $\Delta V^2 \nu_0 [N^2 \rho + N(1-\rho) + N]$;
- For correlated kicks: average amplitude=$\rho N \Delta V$ and average frequency=ν_0/ρ;
- For uncorrelated kicks: frequency=$N\nu_0$ and amplitude= ΔV.

Correlations via common drive

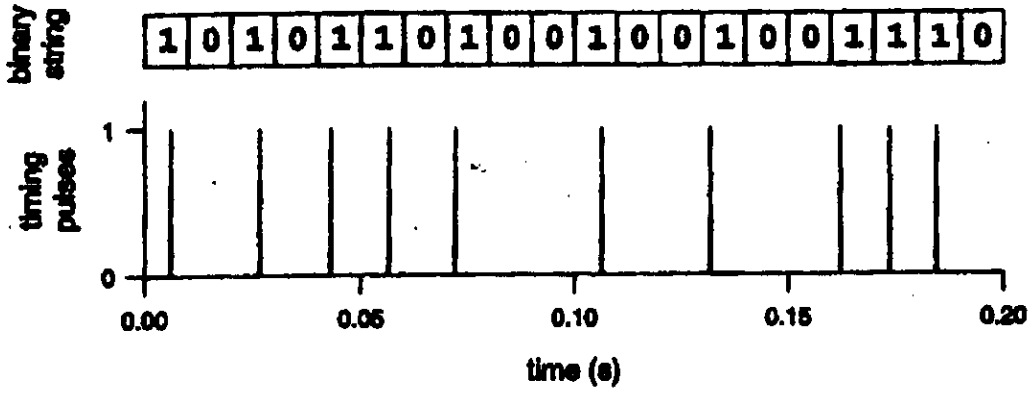
- Correlations only among excitatory or inhibitory inputs are considered in the balanced case $N_E = N_I \equiv N$;
- The superposition of N correlated (ρ) Poissonian spike trains with rate ν_0 gives rise to a sequence of kicks of variable amplitude (binomially distributed) and with ISIs Poissonian distributed with rate ν_0/ρ;
- The average input is not influenced by correlations $< I > \equiv 0$, instead the noise variance is $\Delta V^2 \nu_0 [N^2 \rho + N(1-\rho) + N]$;
- For correlated kicks: average amplitude=$\rho N \Delta V$ and average frequency=ν_0/ρ;
- For uncorrelated kicks: frequency=$N\nu_0$ and amplitude= ΔV.

The correlation between two input spike trains originating from neuron i and j is measured in terms of the Pearson correlation coefficient :

$$\rho = \frac{< (n_i - \langle n_i \rangle)(n_j - \langle n_j \rangle) >}{s^2}$$

where n is the number of spikes in a time window ΔT and s^2 its variance. M.N. Shadlen & W.T. Newsome (1998) – E. Salinas & J. Sejnowski (2000)

Entropie condizionali



- Δt="finestra" temporale $\rightarrow$ *codifica binaria* ("1"/"0") del potenziale di membrana;
- $C_N = (1, 0, 1, \ldots) \rightarrow$ "parola" (o "stato") di lunghezza N;
- $H(N) = -\sum_{\{C_N\}} P(C_N) \log_2 P(C_N)$, "entropia del blocco N";
- $h(N) = H(N+1) - H(N)$, "entropia condizionale" $\rightarrow$ regolarità, prevedibilità:

  (1,0,0,1,0,1,?,...) $\qquad h(N+1) \leq h(N)$

  $h_{max}(N) = \log_2 2 = 1.$