## BME 665/565

## Cascade models and Spike Trains:

Probabilistic Firing and Noise

## Levels of Modeling: Biophysical Models

Level I: Single-compartment models


Hodgkin-Huxley model

$$
\begin{gathered}
C \frac{d V}{d t}=I-\bar{g}_{N a} m^{3} h\left(V-V_{N a}\right)-\bar{g}_{K} n^{4}\left(V-V_{K}\right)-g_{L}\left(V-V_{L}\right) \\
\frac{d m}{d t}=\alpha_{m}(V)(1-m)-\beta_{m}(V) m \quad \frac{d h}{d t}=\alpha_{h}(V)(1-h)-\beta_{h}(V) h \\
\frac{d n}{d t}=\alpha_{n}(V)(1-n)-\beta_{n}(V) n
\end{gathered}
$$

Level II: Detailed compartmental models


Two-dimensional models

$$
\begin{gathered}
\lambda^{2} \frac{\partial^{2} V}{\partial x^{2}}-\tau \frac{\partial V}{\partial t}-V=0 \\
\boldsymbol{\tau}=r_{m} c_{m}, \lambda=\sqrt{\frac{r_{m}}{r_{a}}}
\end{gathered}
$$

## Levels of modeling: Information coding

## Level III: Reduced compartmental models



Integrate-and-fire models

$$
\tau_{\mathrm{m}} \frac{d V}{d t}=E_{\mathrm{L}}-V+R_{\mathrm{m}} I_{\mathrm{e}} \quad \text { If } V>V_{\text {th }} \text {, then } V=V_{\text {reset }}
$$

## Spike Response Models

$$
V(t)=\eta(t-\hat{t})+\int_{0}^{\infty} \kappa(t-\hat{t}, s) I(t-s) \mathrm{d} s
$$

Level IV: Cascade models


## Level V: Black-box models



Rate and timing codes
$r=\frac{n}{T}=\frac{1}{T} \int_{0}^{T} d \tau \rho(\tau) \quad r_{e s t}(t)=r_{0}+\int_{0}^{\infty} D(\tau) s(t-\tau) d \tau$

## Application of information coding approaches

| Biological Goal | Computation | Biophysical <br> Mechanism | Level | Experimental <br> systems |
| :--- | :--- | :--- | :--- | :--- |
| Motion <br> anticipation | Linear filtering with <br> negative feedback | Adaptation of neuronal <br> gain | 4 | Salamander and <br> rabbit retinal <br> ganglion cells |
| Motion <br> detection | Logical AND or AND- <br> NOT comparisons of <br> temporal shifted info | Coincidence detection <br> of one lagged and on <br> nonlagged spike | 4 | Peripheral neurons <br> in the fly visual <br> system |
| Intensity- <br> invariant <br> recognition of <br> patterns | Separation of pattern <br> identity and intensity; <br> compare to stored <br> template | Transformation of local <br> stimulus to spike time; <br> coincidence detection | 1,4 | Insect and <br> vertebrate olfactory <br> neurons |
| Redundancy <br> reduction | Subtraction of local <br> signal minus <br> background signal | Dendritic summation | 4 | Center-surround <br> receptive fields in <br> the visual system |
| Efficient coding <br> in variable <br> environment | Modification of <br> turning curve to track <br> time-varying stimulus <br> ensemble | Adaptation of single- <br> cell input-output <br> function | $3,4,5$ | Motion-sensitive H1 <br> neuron in the fly <br> visual system |
| Adapted from Herz et al., Science. 2006 | Oct 6;314(5796):80-5. |  |  |  |

## Variability in neuronal firing

> Inter-Spike Interval (ISI)


Post-Stimulus Time Histogram (PSTH)



## Neuronal firing patterns (primate PFC)



Adapted from Compte et. al. J Neurophysiol 90: 3441-3454, 2003.

## Modeling variability in firing patterns



## Compartmental models of variability to not match experimental results

- Poisson firing rate
—— Compartmental model with realistic parameters
—— Compartmental model with "Barely Plausible" parameters (all synapses on apical dendrite 60pm from soma, fast and strong EPSP)


Adapted from: Softky + Koch,. J Neuroscience 13(1): 334-350, 1993.

## Homogeneous Poisson process

- Simple random process with no memory: every event is independent of any previous event
- Assume an average cell firing rate $r$
- The firing rate $r$ is the probability of firing a spike in an interval $\Delta t$ around $t$, as $\Delta t \rightarrow 0$
- So, the probability of a single spike occurring in that interval is $r \Delta t$
- Since all spikes are independent of each other, we can express the probability density solely as a function of the number of spikes during an interval
- Take an interval $T$ and divide it into $M$ bins of size $\Delta t$ :

$$
\Delta t=T / M
$$

- Choose $\Delta t$ so that we never get 2 spikes in a single bin


## Homogeneous Poisson process (cont.)

- How do we determine $P_{T}(n)=$ Probability of exactly $n$ spikes occurring during the interval $T$ ?
- $P_{T}(n)$ is the product of:
- The probability of generating $n$ spikes within $M$ bins
- The probability of not generating spikes in the remaining bins
- The number of ways in which $n$ spikes can occur in $M$ bins


## Determining $P_{T}(n)$

- $\quad P_{T}(n)$ is the product of:
- The probability of generating $n$ spikes within $M$ bins
- The probability of not generating spikes in the remaining bins
- The number of ways in which $n$ spikes can occur in $M$ bins
- Since we chose $\Delta t$ to ensure at most one spike per bin, the probability of generating $n$ spikes is equivalent to the probability that $n$ of the $M$ bins contain a spike
- Spikes are independent
- Probability of spike in 1 bin is $r \Delta t$
- So, probability of generating a spike in each of $n$ bins is $(r \Delta t)^{n}$


## Determining $P_{T}(n)$ (cont.)

- $\quad P_{T}(n)$ is the product of:
- The probability of generating $n$ spikes within $M$ bins
- The probability of not generating spikes in the remaining bins
- The number of ways in which $n$ spikes can occur in $M$ bins
- The probability of not having a spike in a given bin is

$$
1-r \Delta t
$$

- The probability of having the remaining M-n bins without any spikes in them is:

$$
(1-r \Delta t)^{M-n}
$$

## Determining $P_{T}(n)$ (cont.)

- $\quad P_{T}(n)$ is the product of:
- The probability of generating $n$ spikes within $M$ bins
- The probability of not generating spikes in the remaining bins
- The number of ways in which $n$ spikes can occur in $M$ bins
- The number of ways of putting n spikes into M bins is given by the binomial coefficient:

$$
\frac{M!}{(M-n)!n!}
$$

## Determining $P_{T}(n)$ (cont.)

- Hence, the probability of $n$ spikes in time $T$ is:

$$
P_{T}(n)=\lim _{\Delta t \rightarrow 0} \frac{M!}{(M-n)!n!}(r \Delta t)^{n}(1-r \Delta t)^{M-n}
$$

- For large M and small n (i.e. Low firing rates), approximate:

$$
(M-n)=M=T / \Delta t \quad \text { and } \quad \frac{M!}{(M-n)!} \approx M^{n}=(T / \Delta t)^{n}
$$

- So,

$$
\lim _{\Delta t \rightarrow 0}(1-r \Delta t)^{M-n}=\lim _{\Delta t \rightarrow 0}(1-r \Delta t)^{M}=\lim _{\Delta t \rightarrow 0}(1-r \Delta t)^{\frac{T}{\Delta t}}=\lim _{\Delta t \rightarrow 0}(1-r \Delta t)^{\frac{-r T}{-r \Delta t}}
$$

## Determining $P_{T}(n)$ (cont.)

- Let: $\varepsilon=-r \Delta t$ and note that by definition $\lim _{\varepsilon \rightarrow 0}\left((1+\varepsilon)^{\frac{1}{\varepsilon}}\right)=e$
- So: $\left.\lim _{\Delta t \rightarrow 0}(1-r \Delta t)^{M-n}=\lim _{\Delta t \rightarrow 0}(1-r \Delta t)^{\frac{-r T}{-r t}}=\lim _{\varepsilon \rightarrow 0}\left((1+\varepsilon)^{\frac{1}{\varepsilon}}\right)^{-r T} \neq e^{-r T}\right)$
- Substitute into:

$$
\begin{aligned}
P_{T}(n) & =\lim _{\Delta t \rightarrow 0} \frac{(T / \Delta t)^{n}}{M-n)!n!}(r \Delta t)^{n}(1-r \Delta t)^{M-n} \\
& =\lim _{\Delta t \rightarrow 0}\left(\frac{T}{\Delta t}\right)^{n} \frac{1}{n!}(r \Delta t)^{n} e^{-r T} \\
& =\lim _{\Delta t \rightarrow 0} \frac{(r T)^{n}}{n!} e^{-r T}
\end{aligned}
$$

## Determining $P_{T}(n)$ (cont.)

- The result is the Poisson distribution: $P_{T}(n)=\frac{(r T)^{n}}{n!} e^{-r T}$

Applying this to Interspike Intervals


Constant input, stationary interval distribution: $P_{0}(t)$ represented by the interspike histogram

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Time-varying input, inputdependent interval distribution: $P_{I}(t \mid \hat{t})$ represents probability density that next spike occurs after an interval $t-\hat{t}$

## Survivor function

- The probability that a spike occurs between time $t_{1}$ and $t_{2}$ is just the integration of the probability density, given by:

$$
\int_{t_{1}}^{t_{2}} P_{I}(t \mid \hat{t}) d t
$$

- The survivor function is the probability that a spike doesn't occur in that interval
- For a spike at time $\hat{t}$ the survivor function is defined as:

$$
S_{I}(t \mid \hat{t})=1-\int_{\hat{t}}^{t} P_{I}\left(t^{\prime} \mid \hat{t}\right) d t^{\prime}
$$

## Hazard function

- The hazard function is the probability of firing at point $t$, given we haven't fired yet
- Defined as the rate of decay of the survivor function:

$$
\rho_{I}(t \mid \hat{t})=\frac{-\frac{d}{d t} S_{I}(t \mid \hat{t})}{S_{I}(t \mid \hat{t})}
$$

Probability of firing at point $t$, given we haven't fired yet


## Hazard function

- How do we interpret this?
- The hazard is a measure of the likelihood of firing given no spike occurred up to time $t$
- Example: reduced hazard at times close to the previous firing is characteristics of a refractory period
- Example: increasing hazard implies that the likelihood of firing increases the longer it has been since the last spike


## Hazard function for a Poisson Process

For the Poisson distribution:

$$
P_{T}(n)=\frac{(r T)^{n}}{n!} e^{-r T}
$$

The probability of not firing a spike $(n=0)$ for a period $t$ is $e^{-r t}$, which is the survivor function

So the hazard function for the Poisson process is simply the (constant) firing rate:

$$
\rho_{I}(t \mid \hat{t})=\frac{-\frac{d}{d t} S_{I}(t \mid \hat{t})}{S_{I}(t \mid \hat{t})}=r
$$




Example: Poisson firing rate, with and without a refractory period



$$
\rho_{I}(t \mid \hat{t})=r \cdot \Theta\left(t-\Delta_{a b s}\right)
$$

Note that this formalization allows us to derive all of these functions if one can be acquired empirically

$$
\begin{aligned}
S_{I}(t \mid \hat{t}) & =1-\int_{\hat{t}}^{t} P_{I}\left(t^{\prime} \mid \hat{t}\right) d t^{\prime} \\
& \Rightarrow P_{I}(t \mid \hat{t})=-\frac{d}{d t} S_{I}(t \mid \hat{t})
\end{aligned}
$$

$$
\rho_{I}(t \mid \hat{t}) S_{I}(t \mid \hat{t})=-\frac{d}{d t} S_{I}(t \mid \hat{t})
$$

$$
\Rightarrow \quad S_{I}(t \mid \hat{t})=\exp \left(-\int_{\hat{t}}^{t} \rho_{I}\left(t^{\prime} \mid \hat{t}\right) d t^{\prime}\right)
$$



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$$
\rho=a_{0}\left(t-\Delta_{a b s}\right)
$$


$\rho=r\left(1-\exp \left(-\lambda\left(t-\Delta_{a b s}\right)\right)\right.$

## Functional relevance of noisy firing rates



Auditory nerve response to pure tone stimulation, in squirrel monkey

ISI shows that neurons do not fire during every period of the stimulus, but miss periods (with an exponentially decreasing likelihood)

## Noisy firing rates improve auditory thresholds



Threshold to produce a spike train without noise is about 0.041 .

With a small amount of noise (s.d. $=0.12$ ) the threshold to spike is reduced to about 0.025

## Noise and firing rates

- If the probability density is a function of noise, the distribution of inter-spike intervals will change

Noisy threshold: define our hazard as a function of the distance from threshold

$$
\rho(t \mid \hat{t})=f[u(t \mid \hat{t})-v]
$$

The function $f$ defines the "escape rate" that causes "jitter" in the firing threshold


## Noisy thresholds

- Consider our leaky integrate-and-fire neuron:

$$
I(t)=C \frac{d V(t)}{d t}+\frac{V(t)}{R} \Longleftrightarrow V(t \mid \hat{t})=R I_{0}\left[1-\exp \left(-\frac{t-\hat{t}}{\tau_{m}}\right)\right]
$$

- Assuming a linear escape rate: $\rho(t \mid \hat{t})=\beta[u(t \mid \hat{t})-v]$

If we let $r=\beta R I_{0}$ and $\lambda=\tau_{m}^{-1} \quad$ then for $v=0$

$$
\rho(t-\hat{t})=r[1-\exp (-\lambda(t-\hat{t}))]
$$





In mammalian auditory neurons, the hazard function increases, after a refractory period, to a constant level


$$
\rho(t-\hat{t})=r[1-\exp (-\lambda(t-\hat{t}))]
$$

## Highly reproducible firing patterns with noisy input



## Noisy inputs leads to increased reliability and precision

Reliability: Fraction of spikes occurring in the peri-stimulus region
Precision: S.D. of spike times within the event


## Gaussian response of IIF neuron

$$
C \frac{d V(t)}{d t}=-\frac{V(t)}{R}+I_{0}+\xi(t) \quad \text { Langevin equation }
$$

Consider a Gaussian additive noise source $\xi$ with probability density


$$
\begin{gathered}
P(V \mid t)=\frac{1}{\sqrt{2 \pi \sigma^{2} t}} \exp \left(-\frac{V^{2}}{2 \sigma^{2} t}\right) \\
\langle\xi(t)\rangle=0
\end{gathered}
$$



## Understanding neuronal responses to stimuli

- We'd like to be able to characterize the properties of the neuronal firing patterns using well-understood statistical methods
- Allows us to examine how different stimuli change the behavior
- Allows us to predict a response to new stimuli
- In order to do this, we must
- Pick an encoding (e.g. firing rate, interval distribution, etc.)
- Characterize it appropriately to derive characteristic properties


## Motion Anticipation: Single neuron response to stimulus



## Population response to flashing and moving bars



After a latency of 40 ms , neural activity increases to a peak at 60 ms . Profile is centered on location of the flashing bar, and has a width at half-maximum that is $\sim$ the size of the receptive field for these neurons

For a moving bar, the neural activity leads the center of the bar by about $100 \mu \mathrm{~m}$.

