

On the Hamiltonian structure of large deviations in stochastic hybrid systems

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Motivations

The example of SDEs (Freidlin and Wentzel 1984, 1998, 2012)

The PDMP model

LDP and action

Ion channels example

Concluding remarks

PDMPs (Davis 1984)

- ▶ The coupling of a piecewise deterministic dynamical system

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- ▶ with a time-homogeneous Markov chain on some discrete space Γ

PDMPs (Davis 1984)

- ▶ The coupling of a piecewise deterministic dynamical system
- ▶ with a time-homogeneous Markov chain on some discrete space Γ
- ▶ produces a hybrid stochastic system or piecewise deterministic Markov process (PDMP)

PDMP example

Membrane voltage fluctuations due to the stochastic opening and closing of ion channels.

- ▶ $\#$ ion channels $\rightarrow \infty$, one recovers, e.g., the H.-H. model (e.g. Pakdaman, Thieullen, Wainrib, 2010, 2012)
- ▶ Finite size effects can result in Spontaneous Action Potentials (SAPs)

Two time scales

- ▶ Transition rates between discrete states in Γ are faster than the relaxation rate of the piecewise deterministic dynamics (ratio of the time constants is ε).
- ▶ Assuming the Markov chain is ergodic, there is a unique stationary measure.
- ▶ In the limit $\varepsilon \rightarrow 0$ the system converges toward a deterministic dynamical system in which one averages the piecewise dynamics w.r.t. this stationary measure.

The question

Characterize how, for $\varepsilon \ll 1$, the law of the underlying stochastic process approaches the deterministic limit.

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Action functional, Lagrangian and Hamiltonian

Consider the 1D SDE

$$dx_t = b(x_t)dt + \varepsilon\sigma(x_t)dw_t$$

- ▶ b, σ are bounded and uniformly continuous. σ is non-degenerate.
- ▶ There exists an LDP for the random path of the SDE over $[0, T]$:

$$P_\varepsilon[x] \sim e^{-J_T(x)/\varepsilon^2}$$

- ▶ J_T is the rate function or the normalized action functional:

$$J_T(x) = \int_0^T L(x, \dot{x}) dt$$

Action functional, Lagrangian and Hamiltonian

- ▶ L is the Lagrangian:

$$L(x, \beta) = \frac{(b(x) - \beta)^2}{2\sigma^2(x)}$$

- ▶ The corresponding Hamiltonian is given by the Legendre transform:

$$H(x, \alpha) = \sup_{\beta} \{\alpha\beta - L(x, \beta)\} = b(x)\alpha + \frac{1}{2}\sigma^2(x)\alpha^2$$

Action functional, Lagrangian and Hamiltonian

Amenable to explicit calculations:

- ▶ Asymptotics for the mean exit time for the neighborhood D of an equilibrium x_0
- ▶ Most probable paths of escape from D

Action functional, Lagrangian and Hamiltonian

Involves a quasi-potential $\Phi(x)$ solution to a Hamilton-Jacobi equation

$$H(x, \Phi'(x)) = 0$$

- ▶ If there is a unique point $y_0 \in \partial D$ minimizing $\Phi(y)$, $y \in \partial D$, then with probability 1, x_t will exit D near y_0 when $\varepsilon \rightarrow 0$.
- ▶ If τ^ε is the first exit time from D

$$\lim_{\varepsilon \rightarrow 0} \varepsilon^2 \log \mathbb{E} \tau^\varepsilon = \min_{y \in \partial D} \Phi(y)$$

where $\tau^\varepsilon = \inf\{t : x_t \in \partial D\}$

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The continuous dynamics

- ▶ State $(x, n) \in \Omega \times \Gamma$, $\Gamma = \{1, \dots, K\}$ discrete set of internal states, Ω open bounded set of \mathbb{R}^d .
- ▶ When the internal state is n the dynamics of x obeys

$$\dot{x} = F_n(x)$$

Some technical conditions:

- ▶ F_n is locally Lipschitz continuous,
- ▶ the vector field $F(x) = (F_1(x), \dots, F_K(x))$ does not have identical components for all $x \in \Omega$,
- ▶ $\partial\Omega$

The discrete dynamics

Given the K^2 functions $W_{mn}(x)$, $\Gamma \times \Gamma \times \Omega \rightarrow \mathbb{R}$ such that

- ▶ $\forall m, n$, $W_{mn}(\cdot)$ is $C^1(\Omega)$
- ▶ $\forall x, m$, $W_{m\cdot}(x)$ is a probability measure on Γ , $W_{nn}(x) = 0$.

The discrete dynamics

- ▶ System starts in state (x_0, n_0) , $x_0(t)$ the solution.
- ▶ Draw the time τ_1 with values in $[0, \infty)$ from the law

$$\frac{1}{\varepsilon} \exp\left(-\frac{t}{\varepsilon}\right)$$

- ▶ In the interval $[0, \tau_1)$ the state is $(x_0(t), n_0)$
- ▶ Draw n_1 from the law $W_{n_0}(\cdot | x_0(\tau_1))$
- ▶ $x_1(t)$ is the solution to the Cauchy problem

$$\begin{cases} \dot{x}_1(t) &= F_{n_1}(t), \quad t \geq \tau_1 \\ x_1(\tau_1) &= x_0(\tau_1) \end{cases}$$

The discrete dynamics

The stochastic process $\{x(t), n(t)\}$ is called a piecewise deterministic stochastic process (PDMP).

Theorem (Harris 1984)

The stochastic process $\{x(t), n(t)\}$ has the strong Markov property.

- ▶ Natural path space is $C([0, T], \Omega) \times D([0, T], \Gamma)$
- ▶ Given (x_0, n_0) in $\Omega \times \Gamma$ we note $\mathbb{P}_{x_0, n_0}^\varepsilon$ the law of the process $(x(t), n(t))$ starting at (x_0, n_0) .

The generator

Its generator is given by

$$Lg(x, n) = F_n(x) \cdot \nabla_x g(x, n) + \frac{1}{\varepsilon} \sum_{m \in \Gamma} W_{nm}(x) (g(x, m) - g(x, n))$$

for regular functions $g : \Omega \times \Gamma \rightarrow \mathbb{R}$.

The generator

We rewrite it as

$$Lg(x, n) = F_n(x) \cdot \nabla_x g(x, n) + \frac{1}{\varepsilon} \sum_{m \in \Gamma} A_{nm}(x) g(x, m)$$

where

$$A_{nm} = W_{nm} - \delta_{nm}$$

Note that

$$\sum_{m \in \Gamma} A_{nm} = 0$$

The averaged dynamics

- ▶ Assume that for every $x \in \Omega$ the matrix $\mathbf{A}(x) = A_{nm}(x)$ is irreducible.
- ▶ There is a unique invariant measure $\rho(x, \cdot)$ satisfying

$$\sum_{m \in \Gamma} A_{nm}(x) \rho(x, m) = 0 \quad \forall n \in \Gamma$$

Define the averaged vector field

$$\bar{F}(x) = \sum_{n \in \Gamma} F_n(x) \rho(x, n)$$

The averaged dynamics

$\bar{F}(x)$ is locally Lipschitz because the $\rho(\cdot, n)$ are C^1 .
The Cauchy problem

$$\begin{cases} \dot{x} &= \bar{F}(x) \\ x(0) &= x_0 \end{cases}$$

has a unique solution for all $x_0 \in \Omega$

The averaged dynamics

Theorem (Faggionato et al. 2009)

Given (x_0, n_0) in $\Omega \times \Gamma$, call $x_*(t)$ the unique solution of the Cauchy problem

$$\begin{cases} \dot{x}_* &= \bar{F}(x_*) \\ x_*(0) &= x_0 \end{cases}$$

Then for every $\delta > 0$, $n \in \Gamma$ and for any continuous function $f : [0, T] \rightarrow \mathbb{R}$ it holds

$$\lim_{\varepsilon \rightarrow 0} \mathbb{P}_{x_0, n_0}^\varepsilon \left(\left| \int_0^T f(t) \chi(n(t) = n) dt - \int_0^T f(t) \rho(x_*(t), n) dt \right| > \delta \right) = 0$$

and

$$\lim_{\varepsilon \rightarrow 0} \mathbb{P}_{x_0, n_0}^\varepsilon \left(\sup_{t \in [0, T]} |x(t) - x_*(t)| > \delta \right) = 0$$

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A Large deviation principle

- ▶ $\mathcal{M}_{0+}([0, T])$ the set of non-negative finite measures on $[0, T]$ absolutely continuous w.r.t. to Lebesgue.

Given the internal state trajectory $\{n(t)\}_{t \in [0, T]}$ associate the K -dimensional vector $\{\psi(t)\}_{t \in [0, T]}$

$$\psi_n(t) = \chi(n(t) = n)$$

A Large deviation principle

Topology:

$$d(\{x(t), \psi(t)\}_{t \in [0, T]}, \{\tilde{x}(t), \tilde{\psi}(t)\}_{t \in [0, T]}) = \sup_{t \in [0, T]} |x(t) - \tilde{x}(t)| + \sum_{n \in \Gamma} \sup_{t \in [0, T]} \left| \int_0^t |\psi_n(s) - \tilde{\psi}_n(s)| ds \right|$$

\mathcal{Y} is compact.

A Large deviation principle

Theorem (Faggionato et al.)

Given (x_0, n_0) in $\Omega \times \Gamma$, the family of laws $\mathbb{P}_{x_0, n_0}^\varepsilon$ on \mathcal{Y} satisfies an LDP with rate function $J : \mathcal{Y} \rightarrow [0, \infty)$ defined by

$$J(x, \psi) = \int_0^T j(x(t), \psi(t)) dt$$

and

$$j(x, \psi) = \sup_{z \in (0, \infty)^\Gamma} \sum_{m, n \in \Gamma} \psi_m W_{nm}(x) \left[1 - \frac{z_m}{z_n} \right]$$

A Large deviation principle

$$\limsup_{\varepsilon \rightarrow 0} \varepsilon \log \mathbb{P}_{x_0, n_0}^\varepsilon(C) \leq -J(C) \quad \forall C \text{ closed } \subset \mathcal{Y}$$

$$\liminf_{\varepsilon \rightarrow 0} \varepsilon \log \mathbb{P}_{x_0, n_0}^\varepsilon(O) \geq -J(O) \quad \forall O \text{ open } \subset \mathcal{Y}$$

A Large deviation principle

By the contraction principle

Theorem (Faggionato et al.)

Given (x_0) in Ω , the family of laws $\mathbb{P}_{x_0}^\varepsilon$ on $C([0, T], \Omega)$ satisfies an LDP with rate function $J_T : C([0, T], \Omega) \rightarrow [0, \infty)$ defined by

$$J_T(x) = \inf_{\{\psi(t)\}_{t \in [0, T]} : \{x(t), \psi(t)\}_{t \in [0, T]} \in \mathcal{Y}} J(x, \psi)$$

A Large deviation principle

Rephrased:

$$\mathbb{P}_{x_0}^\varepsilon \left(\{x(t)\}_{t \in [0, T]} : \{x(t)\}_{t \in [0, T]} \approx \{\hat{x}(t)\}_{t \in [0, T]} \right) \sim e^{-\frac{1}{\varepsilon} J_T(\hat{x})}$$

Our result in 1D (Bressloff and F. 2015)

- ▶ The rate function J_T can be written in the form

$$J_T(\{x(t)\}_{t \in [0, T]}) = \int_0^T L(x, \dot{x}) dt$$

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$$J_T(\{x(t)\}_{t \in [0, T]}) = \int_0^T L(x, \dot{x}) dt$$

- ▶ The Lagrangian

$$L(x, \dot{x}) = \mu(x, \dot{x})\dot{x} - \lambda(x, \mu(x, \dot{x}))$$

Our result in 1D (Bressloff and F. 2015)

- ▶ $\lambda(x, \mu)$ is the Perron eigenvalue of

$$\mathbf{A}(x) + \mu \text{diag}(F_1(x), \dots, F_K(x))$$

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- ▶ $\lambda(x, \mu)$ is the Perron eigenvalue of

$$\mathbf{A}(x) + \mu \text{diag}(F_1(x), \dots, F_K(x))$$

- ▶ $R(x, \mu)$ one corresponding eigenvector.

$\mu = \mu(x, \dot{x})$ is the solution to

$$\dot{x} = \sum_{m \in \Gamma} \psi_m(x, \mu) F_m(x)$$

with

$$\psi(x, \mu) = z(x, \mu) \cdot R(x, \mu)$$

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- ▶ z is a Perron eigenvector of

$$\mathbf{A}'(x) + \mu \text{diag}(F_1(x), \dots, F_K(x))$$

with the normalization

$$\langle z, R \rangle = 1$$

Our result in 1D (Bressloff and F. 2015)

The corresponding Hamiltonian

$$H(x, \alpha) = \sup_{\beta} \{ \alpha \beta - L(x, \beta) \}$$

is equal to

$$H(x, \alpha) = \lambda(x, \alpha)$$

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The neuron model I

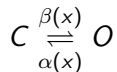
- ▶ Fast sodium channels, N of them

The neuron model I

- ▶ Fast sodium channels, N of them
- ▶ $x(t)$ value of membrane potential at time t

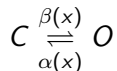
The neuron model I

- ▶ Fast sodium channels, N of them
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- ▶ Each channel can only be open (O) or closed (C)



The neuron model I

- ▶ Fast sodium channels, N of them
- ▶ $x(t)$ value of membrane potential at time t
- ▶ Each channel can only be open (O) or closed (C)



- ▶ Piecewise deterministic equation

$$\dot{x}(t) = F_n(x) = \frac{n}{N} f(x) - g(x)$$

$$f(x) = g_{Na}(V_{Na} - x) \quad g(x) = -g_L(V_l - x) - I$$

The neuron model II

$$\Gamma = \{0, 1, \dots, N\}$$

Markov chain obtained from the birth-death process

$$n \xrightarrow{\omega_+(n,x)/\varepsilon} n+1, \quad n \xrightarrow{\omega_-(n,x)/\varepsilon} n-1$$

with transition rates

$$\omega_+(x, n) = \alpha(x)(N - n), \quad \omega_-(x, n) = \beta(x)n.$$

The matrix \mathbf{A} is tridiagonal

The neuron model III

The Markov chain is ergodic with unique invariant measure

$$\rho(x, n) = \frac{N!}{(N-n)!n!} a(x)^n b(x)^{N-n},$$

with

$$a(x) = \frac{\alpha(x)}{\alpha(x) + \beta(x)}, \quad b(x) = \frac{\beta(x)}{\alpha(x) + \beta(x)}.$$

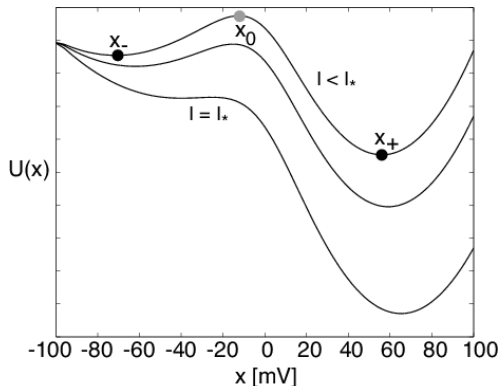
Deterministic kinetic equation

$$\dot{x} = a(x)f(x) - g(x)$$

$$a(x) = \langle n \rangle / N \quad \langle n \rangle = \sum_{n \in \Gamma} n \rho(x, n)$$

The neuron model IV

The averaged model can exhibit bistability:



x_- resting state

x_+ active state

The neuron model V

Transitions from x_- to x_+ can be interpreted as initiating spontaneous action potentials.

The Hamiltonian $H(x, \alpha)$ can be computed:

$$H(x, \alpha) = \alpha[-N\beta(x)g(x) + (N\alpha(x) + \alpha g(x))(f(x) - g(x))]$$

and so does the quasi-potential Φ solution of

$$H(x, \Phi'(x)) = 0$$

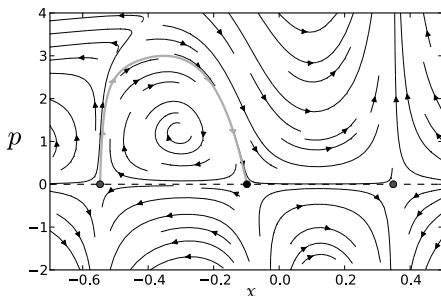
Two solutions are found:

$$\Phi'(x) = 0 \quad \Phi'(x) = -N \frac{\alpha(x)f(x) - (\alpha(x) + \beta)g(x)}{g(x)(f(x) - g(x))}$$

The neuron model VI

- ▶ $\Phi = \text{constant}$ corresponds to deterministic trajectories converging to x_- .
- ▶ Non-trivial solution for Φ corresponds to the most likely escape trajectory.

Solutions to Hamilton's equations in the (x, α) plane:



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Some remarks

- ▶ Useful alternative to the Wentzel-Kramers-Brillouin (WKB) method, especially in dimensions larger than 1.
- ▶ "Easy" extension to the case where the slow process is a piecewise SDE.
- ▶ Use these ideas to model the pathologic gating induced by mutations of ion channels (found in epilepsy, migraine and neuropathic pain).