

Limiting Behavior of Stationary Measures for Stochastic Evolution Systems

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Outline

- 1 Introduction
- 2 General Framework
 - Basic Assumption: Probability Convergence (PC)
 - Main Result
- 3 Applications
 - SOEDs
 - SFDEs
 - SPDEs
- 4 Two Examples
 - Example 1: The Bernoulli Lemniscate System
 - Example 2: The May-Leonard System

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Motivation

“A major step in making the equation more relevant is to add a small stochastic term. ... It seems fair to say that all differential equations are better models of the world when a stochastic term is added and that their classical analysis is useful only if it is **stable in an appropriate sense to such perturbations**”. (David Mumford, the Fields Medal in 1974 and the Wolf Prize in 2008)

Problem: How to reveal the connections between deterministic systems and their stochastic perturbation systems ?

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Problem: How to reveal the connections between deterministic systems and their stochastic perturbation systems ?

Some Works on Zero-Noise Limits

- Freidlin and Wentzell, 1979
 - For the non-degenerate diffusion case, via large-deviation technique to estimate the concentration
- P. Dupuis, E.s. Eills, 1997
 - a weak convergence approach to the theory of Large deviations
- Chii-Ruey Hwang, 1980, Ann. Probability
 - Gibbs measures for gradient system with additive noise
- Tu Sheng Zhang, etc
 - large-deviation on SPED with small perturbation

Some Works on Zero-Noise Limits-Continued

- Lai-Sang, Young 2002, 2005, J. Statis. Physics, Ergod. Th. & Dynam. Sys.
 - SRB measures can be realized
- Huang, Ji, Liu and Yi, 2015, 2016, Ann. Probability, Physica D
 - ODE + small white noise, including gradient systems
- Yao Li and Ying Fei Yi, 2016, Comm. Pure Appl. Math.
 - Study the systematic measures of biological network
- and so on ...

Heuristics

The weak limits of the stationary measures for small random perturbations systems represent idealizations of what we want to see.

Problem Statement

Objects

- ϵ — the noise intensity which is small;
- $X^\epsilon(t, x)$ — solution of stochastic differential equations driven by Lévy noise with the intensity ϵ ;
- $\Phi(t, x) := X^0(t, x)$ — the corresponding deterministic dynamical system while $\epsilon = 0$;
- The map $\Phi : \mathbb{R}_+ \times M \rightarrow M$ is called the *dynamical system* if the following properties hold:
 - (i) $\Phi_t(x)$ are continuous, for all $t \in \mathbb{R}_+, x \in M$,
 - (ii) $\Phi_0 = \text{id}$, $\Phi_t \circ \Phi_s(x) = \Phi_{t+s}(x)$, for all $t, s \in \mathbb{R}_+, x \in M$. Here \circ denotes composition of mappings.
- Probability measures μ^ϵ and μ on $\mathcal{B}(M)$ are called *stationary* or *invariant* with respect to $\{P_t^\epsilon\}_{t \geq 0}$ and $\{\Phi_t\}_{t \geq 0}$, respectively, if

$$P_t^\epsilon \mu^\epsilon = \mu^\epsilon \text{ for any } t \geq 0, \text{ and}$$

$$\mu \circ \Phi_t^{-1} = \mu \text{ for any } t \geq 0, \text{ respectively.}$$

Problem Statement-Continued

Objects

- \mathcal{I}^ϵ — stationary measures for $X^\epsilon(t, x)$. $\mathcal{I} := \bigcup_{0 < \epsilon \leq \epsilon_0} \mathcal{I}^\epsilon$;
- \mathcal{M}_L — weak limits: $\mu^{\epsilon_i} \xrightarrow{w} \mu$ as $\epsilon_i \rightarrow 0$;
- $\mathcal{S} := \overline{\{\text{supp}(\mu) : \mu \in \mathcal{M}_L\}}$.

Problems

- The most important questions are now what the **contraction** of \mathcal{S} is ? and how the **dynamics** on $(\mathcal{S}, \Phi|_{\mathcal{S}})$ is ?

\mathcal{S} is contained in the Birkhoff Center

$$B(\Phi) := \overline{\{x \in M : x \in \omega(x)\}}.$$

which responds to the complexity of dynamical system.

- What kind of invariant measures for dynamical system can be approximated by stationary measures for small perturbations systems ?

Strongly depends on the type of noise.

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Concrete Noise Perturbed Processes

- **SODEs Driven by a Lévy process:**

$$\begin{aligned}
 dX^{\epsilon,x}(t) = & b(X^{\epsilon,x}(t))dt + \epsilon\sigma(X^{\epsilon,x}(t))dW_t \\
 & + \epsilon \int_{|y|_{\mathbb{R}^l} < c} F(X^{\epsilon,x}(t-), y) \tilde{N}(dt, dy)
 \end{aligned} \tag{1.1}$$

with initial condition $X^{\epsilon,x}(0) = x \in \mathbb{R}^m$ and $\epsilon, c > 0$. The mappings $b : \mathbb{R}^m \rightarrow \mathbb{R}^m$, $\sigma : \mathbb{R}^m \rightarrow L_2(\mathbb{R}^k, \mathbb{R}^m)$, and $F : \mathbb{R}^m \times \mathbb{R}^l \rightarrow \mathbb{R}^m$ satisfy the some normal conditions.

Concrete Noise Perturbed Processes-Continued

- **Stochastic Reaction Diffusion Equation**

$$\left\{ \begin{array}{l} dX(t, x) = \nu \Delta X(t, x) dt + g(x, X(t, x)) dt \\ \quad + \epsilon \sigma(x, X(t, x)) dW(t), \\ X(t, x) = 0, \quad x \in \partial\Lambda, \quad t > 0, \\ X(0) = h \in L^2(\Lambda). \end{array} \right. \quad (1.2)$$

Here $\nu > 0$, $g : \Lambda \times \mathbb{R} \rightarrow \mathbb{R}$ and $\sigma : \Lambda \times \mathbb{R} \rightarrow l^2$ are two measurable functions. $W(t) = (W_k(t))_{k \in \mathbb{N}}$ is a sequence of independent one dimensional standard Brownian motions.

Concrete Noise Perturbed Processes-Continued

- **2D Stochastic Navier-Stokes Equation Driven by Lévy Noise**

$$dX_t^{\epsilon,h} = (\nu AX_t^{\epsilon,h} + X_t^{\epsilon,h} \cdot \nabla X_t^{\epsilon,h} + h_0(X_t^{\epsilon,h}))dt + \epsilon B(X_t^{\epsilon,h})dW_t + \epsilon \int_Z f(X_{t-}^{\epsilon,h}, z)\tilde{N}(dt, dz), \quad (1.3)$$

$$\operatorname{div}X_t^{\epsilon,h} = 0.$$

with a initial value $X_0^{\epsilon,h} = h$.

Concrete Noise Perturbed Processes-Continued

- 1D Stochastic Burgers Equation Driven by Lévy Noise

$$\begin{aligned}
 dX_t^{\epsilon,h} = & (\Delta X_t^{\epsilon,h} + X_t^{\epsilon,h} \cdot \nabla X_t^{\epsilon,h}) dt \\
 & + \epsilon B(X_t^{\epsilon,h}) dW_t + \epsilon \int_Z f(X_{t-}^{\epsilon,h}, z) \tilde{N}(dt, dz),
 \end{aligned} \tag{1.4}$$

with initial value $X_0^{\epsilon,h} = h$.

Concrete Noise Perturbed Processes-Continued

- **Stochastic Functional Differential Equations (SFDEs)**

$$\begin{aligned}dX^{\epsilon, \phi}(t) &= b(X_t^{\epsilon, \phi})dt + \epsilon\sigma(X_t^{\epsilon, \phi})dW(t), \\ X_0^{\epsilon, \phi} &= \phi \in \mathcal{C} := C([- \tau, 0], \mathbb{R}^m),\end{aligned}\tag{1.5}$$

where $W = \{W_t = (W_t^1, \dots, W_t^k), t \geq 0\}$ is a k -dimensional Wiener process, $b(\cdot) : \mathcal{C} \rightarrow \mathbb{R}^m$ and $\sigma(\cdot) : \mathcal{C} \rightarrow \mathbb{R}^{m \times k}$ satisfy the regular conditions.

Basic Assumption

Let (M, ρ) be a Polish space, $(\Omega, \mathcal{F}, \mathbb{P})$ a probability space. Assume that $X^\epsilon(t, x)$ and $\Phi(t, x)$ are noise driven process and deterministic semi dynamical system on (M, ρ) , respectively.

Hypothesis (PC)

For any $T > 0, \delta > 0$ and compact set $K \subset M$, one has

$$\limsup_{\epsilon \rightarrow 0} \sup_{x \in K} \mathbb{P}\{\rho(X^\epsilon(T, x), \Phi(T, x)) \geq \delta\} = 0.$$

Main Result

The probability transition function

$$P_t^\epsilon(x, A) = \mathbb{P}(X^\epsilon(t, x) \in A), t \geq 0, x \in M, A \in \mathcal{B}(M).$$

Theorem 1 (Φ -Invariance)

Assume that (PC) holds. Let μ^{ϵ_i} be a sequence of invariant probability measure. If $\mu^{\epsilon_i} \xrightarrow{w} \mu$ as $\epsilon_i \rightarrow 0$, then μ is Φ -invariant.

Corollary (Birkhoff, Poincaré and Conley)

If μ is Φ -invariant, then $\text{supp}(\mu)$ is positively invariant for Φ , and

$$\text{supp}(\mu) \subset B(\Phi) = \overline{\{x \in M : x \in \omega(x)\}} - \text{Birkhoff Center.}$$

SODEs Driven by a Lévy Process

$$\begin{aligned}
 dX^{\epsilon,x}(t) = & b(X^{\epsilon,x}(t))dt + \epsilon\sigma(X^{\epsilon,x}(t))dW_t \\
 & + \epsilon \int_{|y|_{\mathbb{R}^l} < c} F(X^{\epsilon,x}(t-), y) \tilde{N}(dt, dy). \tag{3.1}
 \end{aligned}$$

For a C^2 scalar function V and $\epsilon \geq 0$, define an operator

$$\begin{aligned}
 \mathcal{L}^\epsilon V(x) := & \langle \nabla V(x), b(x) \rangle + \frac{\epsilon^2}{2} \sum_{i,j=1}^m a_{ij}(x) \frac{\partial^2 V(x)}{\partial x_i \partial x_j} \\
 & + \int_{|y|_{\mathbb{R}^l} < c} (V(x + \epsilon F(x, y)) - V(x) - \langle \nabla V(x), \epsilon F(x, y) \rangle) \nu(dy),
 \end{aligned}$$

where $A(x) = (a_{ij}(x)) = \sigma(x)\sigma^T(x)$ is the diffusion matrix.

SODEs Driven by a Lévy Process-Continued

Theorem 3 (Support on weak limits)

Let $b(x)$, $\sigma(x)$ and $F(x, y)$ in (3.1) be locally Lipschitz continuous. Suppose that there exists a nonnegative function $V(x) \in C^2(\mathbb{R}^m)$ such that

$$\inf_{|x|>R} V(x) \rightarrow +\infty, \quad \text{as } R \rightarrow \infty, \quad \text{and} \quad (3.2)$$

$$\sup_{|x|>R} \mathcal{L}^\epsilon V(x) \leq -A_R \rightarrow -\infty \text{ as } R \rightarrow \infty. \quad (3.3)$$

Then

- (1) (PC) holds.
- (2) There exists an invariant probability measure μ_x^ϵ for $\epsilon > 0, x \in \mathbb{R}^m$.
- (3) There exists $\mu_x^{\epsilon_i} \in \mathcal{I}^{\epsilon_i}$ such that $\mu_x^{\epsilon_i} \xrightarrow{w} \mu_x$ as $\epsilon_i \rightarrow 0$.

SODEs Driven by a Lévy Process-Continued

In fact,

Lemma (Sufficient conditions for (PC))

Let b , σ and F be locally Lipschitz continuous. If there exist a nonnegative function $V(x) \in C^2(\mathbb{R}^m)$, $\epsilon_0 > 0$ and a constant $c^ < +\infty$, such that (3.2) and*

$$\mathcal{L}^\epsilon V(x) \leq c^* V(x), \quad \forall \epsilon \in [0, \epsilon_0] \quad (3.4)$$

hold. Then there exists a global unique solution $X^{\epsilon,x}(t)$ to (3.1) for all $x \in \mathbb{R}^m$, $\epsilon \in [0, \epsilon_0]$. Moreover the (PC) holds.

Sketch of the Proof

- The global existence and uniqueness of solution to (3.1) are similar as the proof in Khasminskii.
- Let $\tau_n^{\epsilon,x} = \inf\{t : |X^{\epsilon,x}(t)| > n\}$, $\tau_n^{0,x} = \inf\{t : |X^{0,x}(t)| > n\}$ & $S^n(r)$ be a nonincreasing C^∞ function with values in $[0, 1]$ such that

$$S^n(r) = \begin{cases} 1 & \text{if } r \in [0, n], \\ \frac{n+\frac{1}{2}}{r} & \text{if } r \in [n+1, +\infty). \end{cases}$$

Construct functions

$$b_n(x) = b(xS^n(|x|)), \quad (3.5)$$

$\sigma_n(x)$ and $F_n(x, y)$ similarly. Then $b_n(x)$, $\sigma_n(x)$ and $F_n(x, y)$ satisfy global Lipschitz and linear growth conditions.

Sketch of the Proof-Continued

Let $X_n^{\epsilon,x}(t)$ be the solution associated with functions $b_n(x)$, $\sigma_n(x)$ and $F_n(x, y)$. Then $X^{\epsilon,x}(t) = X_n^{\epsilon,x}(t)$ for $t \leq \tau_n^{\epsilon,x}$. For large n , $\sup_{x \in K} \mathbb{P}(\tau_n^{\epsilon,x} \leq T)$ is sufficiently small & $\inf_{x \in K} \tau_n^{0,x} > T$. Therefore,

$$\begin{aligned} & \sup_{x \in K} \mathbb{P}\{|X^{\epsilon,x}(T) - X^{0,x}(T)| \geq \delta\} \\ & \leq \sup_{x \in K} \mathbb{P}\{|X_n^{\epsilon,x}(T) - X_n^{0,x}(T)| \geq \delta, T < \tau_n^{\epsilon,x} \wedge \tau_n^{0,x}\} \\ & \quad + \sup_{x \in K} \mathbb{P}(\tau_n^{\epsilon,x} \wedge \tau_n^{0,x} \leq T) \\ & \leq \frac{1}{\delta^2} \sup_{x \in K} \mathbb{E}|X_n^{\epsilon,x}(T) - X_n^{0,x}(T)|^2 + \sup_{x \in K} \mathbb{P}(\tau_n^{\epsilon,x} \leq T) \rightarrow 0, \text{ as } \epsilon \rightarrow 0. \end{aligned}$$

SODEs Driven by a Lévy Process

Lemma (The existence and tightness of stationary measure)

Suppose that $b(x)$, $\sigma(x)$ and $F(x, y)$ in (3.1) are locally Lipschitz continuous, and that there exists a scalar function $V(x) \in C^2(\mathbb{R}^m, \mathbb{R}_+)$ such that (3.2) and (3.3) hold. Then \mathcal{I}^ϵ is nonempty, and the set $\mathcal{I} = \bigcup_{0 < \epsilon \leq \epsilon_0} \mathcal{I}^\epsilon$ of stationary measures is tight.

The idea of the proof is borrowed from Khasminskii to prove the existence of stationary measures. Using Portmanteau Theorem to prove the tightness.

Nonlinear Case: Polynomial Growth

Corollary

Suppose that $b(x)$, $\sigma(x)$ and $F(x, y)$ in (3.1) are locally Lipschitz continuous. If there are positive constants c_1, c_2 and $q \geq 2$ such that for $|x|$ sufficiently large, one has

$$\langle b(x), x \rangle \leq -c_1|x|^q,$$

$$\frac{1}{2}\|\sigma(x)\|_2^2 + \int_{|y|_{\mathbb{R}^l} < c} |F(x, y)|^2 \nu(dy) \leq c_2|x|^q,$$

then the conclusions of **Theorem 3** hold.

Proof Note that $V(x) = \frac{1}{2}|x|^2$.

Nonlinear Case: Monotone Cyclic Feedback Systems

Consider a typical monotone cyclic feedback system driven by Lévy process

$$\begin{aligned}
 dx^i(t) = & \left[-b_i x^i(t) + f^i(x^{i+1}(t)) \right] dt \\
 & + \epsilon \sum_{j=1}^k \sigma_{ij}(x(t)) dW_j(t) + \epsilon \int_{|y|_{\mathbb{R}^l} < c} F^i(x(t-), y) \tilde{N}(dt, dy),
 \end{aligned}
 \tag{3.6}$$

where b_i is positive constant, f^i is bounded and continuously differentiable with bounded derivative for $i = 0, 1, \dots, N$, $(N + 1) \times k$ -dispersion matrix $\sigma(x) = (\sigma_{ij}(x))$ and F have global Lipschitz continuous and linear growth properties.

Nonlinear Case: Monotone Cyclic Feedback Systems

Note Let $V(x) = \frac{1}{2}|x|^2$, it is easy to see that the assumptions of **Theorem 3** hold, therefore $\mathcal{S} \subset B(\Phi)$. Furthermore,

Theorem 7 (Mallet-Paret and Smith, 2002)

Let $\Phi(t)$ be a solution of unperturbed system (3.6) on $[0, \infty)$. Then $B(\Phi) = \mathcal{E} \cup \mathcal{P}$. More precisely, either

- (1) $\omega(x)$ is a single non-constant periodic orbit; or*
- (2) for solutions with $u(t) \in \omega(x)$ for all $t \in \mathbb{R}$, we have that*

$$\alpha(u) \cup \omega(u) \subset \mathcal{E}.$$

Here

- \mathcal{E} and \mathcal{P} denote the set of equilibria and nontrivial periodic orbits, respectively.
- $\alpha(x)$ and $\omega(x)$ denote the α - and ω -limit sets of solution in the phase space \mathbb{R}^{N+1} , respectively.

FDE: Hopfield Neural Network Models

Consider the stochastic delayed Hopfield equations

$$dX^\epsilon(t) = [-BX^\epsilon(t) + Ag(X^\epsilon(t - \tau))]dt + \epsilon\sigma(X_t^\epsilon)dW(t) \quad (3.7)$$

where $B = \text{diag}(b_1, \dots, b_m)$, $g(x) = (g_1(x_1), \dots, g_m(x_m))^T$, $A = (a_{ij})_{m \times m}$, and $\sigma(\phi) = (\sigma_{ij}(\phi))$ is an $m \times m$ matrix defined on $\mathcal{C} = C([- \tau, 0], \mathbb{R}^m)$.

Assumptions on g and σ :

(A₁) There exists a positive constant \tilde{L}, M such that for all $x, y \in \mathbb{R}^m$

$$|g(x) - g(y)| \leq \tilde{L}|x - y|, \quad |g(x)| \leq M.$$

(A₂) There exists a positive constant L such that for all $\phi, \psi \in \mathcal{C}$

$$\|\sigma(\phi) - \sigma(\psi)\|_2 \leq L\|\phi - \psi\|.$$

(A₃) The diffusion matrix $\sigma\sigma^T$ is *uniformly elliptic* in \mathcal{C}

FDE: Hopfield Neural Network Models

Theorem 8

Assume $(A_1) - (A_3)$. Let $\gamma = 9\left[\frac{2\sqrt{\kappa-1}}{(\sqrt{\kappa-1})^2} + 1\right]$. If

$$\min_{1 \leq i \leq m} b_i > \frac{\gamma^2 e^{6\tau} (16\tilde{L}^3 |A|^3)^2}{(1 - \kappa e^{-3\tau})^2}, \kappa \in (1, e^{3\tau}), \quad (3.8)$$

then

(1) for each $\epsilon \in (0, 1]$, the system (3.7) has a unique invariant measure μ^ϵ for the segment process $\{X_t^\epsilon\}_{t \geq 0}$.

(2) μ^ϵ weakly converges to δ_p as $\epsilon \rightarrow 0$, where p is a globally asymptotically stable equilibrium for differential equations (3.7) with $\epsilon = 0$.

Stochastic Reaction Diffusion Equation with a Polynomial Nonlinearity

Let $\Lambda \subset \mathbb{R}$ be a bounded domain with smooth boundary $\partial\Lambda$,

$$g(u) = \sum_{i=0}^{2k-1} a_i u^i, \quad a_{2k-1} < 0. \quad (3.9)$$

Stochastic reaction diffusion equation with Dirichlet boundary conditions:

$$\begin{cases} dX(t, x) = \Delta X(t, x)dt + g(X(t, x))dt + \epsilon\sigma(x, X(t, x))dW(t), \\ X(t, x) = 0, \quad x \in \partial\Lambda, \quad t > 0, \\ X(0) = h \in L^2(\Lambda). \end{cases} \quad (3.10)$$

Here $\sigma : \Lambda \times \mathbb{R} \rightarrow l^2$ is measurable function.

Stochastic Reaction Diffusion Equation with a Polynomial Nonlinearity-Continued

(C) There exist $c_1, c_2 > 0$ and $h \in L^1(\Lambda)$ such that for all $u, u' \in \mathbb{R}$ and $x \in \Lambda$,

$$\begin{aligned} \|\sigma(x, u) - \sigma(x, u')\|_{l^2}^2 &\leq c_1 |u - u'|^2, \\ \|\sigma(x, u)\|_{l^2}^2 &\leq c_2 |u|^2 + h(x). \end{aligned}$$

Theorem 9

Assume that g is given in (3.9) and σ satisfies condition (C), then any limiting measures of stationary measures for (3.10) are supported in the set of equilibrium points \mathcal{E} of (3.10) with $\epsilon = 0$.

Important facts: Deeply Depends on the Type of Noise

Suppose that $X^{0,x_0}(t)$ is a bounded solution of $\dot{x} = b(x)$.

Denote by \mathcal{I}_{x_0} the set of invariant measures generated by the family of probability measures

$$P^{0,t}(x_0, B) = \frac{1}{t} \int_0^t \delta_{X^{0,x_0}(s)}(B) ds$$

via Krylov-Bogoliubov procedure.

Choose $r = r(x_0) > 0$ such that $\overline{\gamma^+(x_0)} = \overline{\{X^{0,x_0}(t) : t \geq 0\}} \subset B_r(O)$.
Then construct a C^∞ diffusion term σ :

$$\sigma(x) = \begin{cases} \text{zero matrix } 0 & \text{if } x \in B_r(O), \\ \text{constant matrix } J & \text{if } x \in (\bar{B}_{r+1}(O))^c. \end{cases}$$

Important facts: Deeply Depends on the Type of Noise-Continued

Then for SDEs

$$dX^{\epsilon, x_0}(t) = b(X^{\epsilon, x_0}(t))dt + \epsilon\sigma(X^{\epsilon, x_0}(t))dW_t, \quad X^{\epsilon, x_0}(0) = x_0 \quad (4.1)$$

has a unique solution $X^{\epsilon, x_0} = X^{0, x_0}$.

Furthermore, we have

Facts

$X^{\epsilon, x_0}(t) = X^{0, x_0}(t)$ for all $t \geq 0$ and $\mathcal{I}_{x_0} \subset \mathcal{I}$ for all ϵ . In particular, for any $\mu^{\epsilon, x_0} = \mu \in \mathcal{I}_{x_0}$, one has $\mu^{\epsilon, x_0} \xrightarrow{w} \mu$ as $\epsilon \rightarrow 0$.

Important facts: Deeply Depends on the Type of Noise-Continued

Theorem 10 (Uniquely ergodic)

Suppose the assumptions of Theorem 3 are satisfied. If the matrix

$$a(x) := \sigma(x)\sigma^T(x) \quad \text{is invertible,} \quad (4.2)$$

then the semigroup P_t is irreducible. Furthermore, if

- (a) for any $n > 1$, there exists a nonnegative function $c_n \in L^2(\mathbb{R}^l, \mathcal{B}(\mathbb{R}^l), \nu)$ such that $\sup_{|x| \leq n} |F(x, y)| \leq c_n(y)$, $y \in \mathbb{R}^l$,
- (b) there exist positive constants C and C_r for any $r > 0$ such that

$$\int_{|y|_{\mathbb{R}^l} < c} \|D_x F(0, y)\|_2^2 \nu(dy) \leq C,$$

$$\int_{|y|_{\mathbb{R}^l} < c} \|D_x F(x_1, y) - D_x F(x_2, y)\|_2^2 \nu(dy) \leq C_r |x_1 - x_2|^2, \quad |x_1| \vee |x_2| \leq r,$$

then the semigroup P_t has the strong Feller property.

Example 1: The Bernoulli Lemniscate System

Example (The Bernoulli Lemniscate System)

Let $I(x, y) = (x^2 + y^2)^2 - 4(x^2 - y^2)$. Define

$$V(I) := \frac{I^2}{2(1 + I^2)^{\frac{3}{4}}}, \quad H(I) := \frac{I}{(1 + I^2)^{\frac{3}{8}}}.$$

Consider the vector field

$$b(x, y) := - \left[\nabla V(I) + \left(\frac{\partial H(I)}{\partial y}, -\frac{\partial H(I)}{\partial x} \right)^T \right].$$

For the deterministic system

$$\begin{cases} \frac{dx}{dt} = b_1(x, y), \\ \frac{dy}{dt} = b_2(x, y). \end{cases} \quad (4.3)$$

The global behavior of (4.3) are sketched in following Figure.

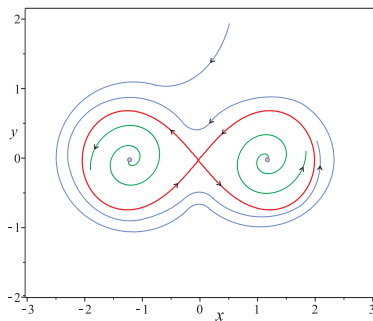


Figure: The phase portrait of (4.3) with $b(x, y) = -\nabla V(x, y) - \Theta(x, y)$.

The Birkhoff center $B(\Phi) = \{O(0, 0), P^+(\sqrt{2}, 0), P^-(-\sqrt{2}, 0)\}$, where O is a saddle point, P^+ , P^- are unstable spirals.

Proposition

The system (4.3) has the equilibria $O(0,0)$, $P^+(\sqrt{2},0)$ and $P^-(-\sqrt{2},0)$. $V(I)$ is its Lyapunov function.

(1) The Birkhoff center $B(\Phi) = \{O, P^+, P^-\}$.

(2) When the initial point p locates outside of the Bernoulli Lemniscate:

$$L : (x^2 + y^2)^2 = 4(x^2 - y^2), \quad (4.4)$$

its ω -limit set $\omega(p) = L$, which is a red curve in Figure;

(3) When the initial point $p \neq P^-$ (resp. $p \neq P^+$) locates left (resp. right) inside of the Bernoulli Lemniscate, its ω -limit set the left (resp. right) branch of L .

For the perturbed system driven by Brownian motion:

$$\begin{cases} dx = b_1(x, y)dt + \epsilon[\sigma_{11}(x, y)dW_t^1 + \sigma_{12}(x, y)dW_t^2], \\ dy = b_2(x, y)dt + \epsilon[\sigma_{21}(x, y)dW_t^1 + \sigma_{22}(x, y)dW_t^2]. \end{cases} \quad (4.5)$$

Theorem 12

Suppose that $\sigma_{ij}(i, j \in \{1, 2\})$ satisfies global Lipschitz condition, thus there exist nonnegative constants C_1, C_2 such that

$$|a_{ij}(x, y)| = |(\sigma(x, y)\sigma^T(x, y))_{ij}| \leq C_1|(x, y)|^2 + C_2, \text{ for } i, j = 1, 2,$$

(i) if $C_1 = 0$, then for any ϵ , the system (4.5) admits at least one stationary measure μ^ϵ ;

(ii) if $C_1 > 0$, then the system (4.5) possesses at least one stationary measure μ^ϵ for $0 < \epsilon < \frac{1}{8\sqrt{26C_1}}$.

If, in addition, the diffusion matrix $a(x, y)$ is positively definite everywhere, then for a given ϵ as above, the stationary measure μ^ϵ is unique, and $\mu^\epsilon \xrightarrow{w} \delta_O(\cdot)$ as $\epsilon \rightarrow 0$, where O is a saddle point.

Sketch of the Proof

- 1 The conclusions of Theorem 3 hold because of the following fact

$$\mathcal{L}^\epsilon V(x, y) \leq -\left[\frac{1}{4\sqrt{2}} - 208\sqrt{2}C_1\epsilon^2\right]r^2 + 208\sqrt{2}C_2\epsilon^2 \rightarrow -\infty \text{ as } r \rightarrow \infty.$$

This implies (i), (ii) and $\text{supp}(\mu) \subset \{O, P^+, P^-\}$, where μ is the weak limit measure.

- 2 Also the uniqueness of μ^ϵ follows from Theorem 10.
- 3 To show $\mu(\{P^+, P^-\}) = 0$.

By the measure estimate theorem [Huang-Ji-Liu-Yi], it is easy to see that

$$\mu^\epsilon(\Omega_{\rho_0}) \leq \mu^\epsilon(\Omega_\rho) e^{-\frac{\tilde{m}}{M} \int_{\rho_0}^\rho \frac{1}{t} dt} \leq e^{-\frac{\tilde{m}}{M} \int_{\rho_0}^\rho \frac{1}{t} dt}, \quad \rho \in (\rho_0, \rho_M).$$

Then, using the fact of $\mu^\epsilon \xrightarrow{w} \mu$ and the openness of Ω_{ρ_0} . Finally, letting $\rho_0 \rightarrow 0$, one has $\mu(\{P^+\}) = 0$.

Example 2: The May-Leonard System

Example (The May-Leonard system)

Consider the May-Leonard system with a white noise perturbation:

$$\begin{cases} dy_1 = y_1(1 - y_1 - \beta y_2 - \gamma y_3)dt + \epsilon y_1 \circ dW_t, \\ dy_2 = y_2(1 - y_2 - \beta y_3 - \gamma y_1)dt + \epsilon y_2 \circ dW_t, \\ dy_3 = y_3(1 - y_3 - \beta y_1 - \gamma y_2)dt + \epsilon y_3 \circ dW_t, \end{cases} \quad (4.6)$$

where \circ denotes the Stratonovich stochastic integral, $\beta, \gamma > 0$ and ϵ denotes noise intensity.

Stochastic Decomposition Formula

Theorem 14 (Chen, Dong, Jiang, Niu and Zhai)

Let Φ^ϵ , Φ^0 be the solutions of (4.6) and the corresponding deterministic system without noise, respectively. Then

$$\Phi^\epsilon(t, \omega, y) = g^\epsilon(t, \omega, g_0) \Phi^0\left(\int_0^t g^\epsilon(s, \omega, g_0) ds, \frac{y}{g_0}\right), \quad (4.7)$$

where g^ϵ is the solution of stochastic logistic equation

$$dg = g(1 - g)dt + \epsilon g \circ dW_t. \quad (4.8)$$

Asymptotic Properties for Φ^0

- M. Hirsch (1988) pointed out that the flow Φ^0 admits an invariant surface Σ (called *carrying simplex*), such that every trajectory in $\mathbb{R}_+^3 \setminus \{O\}$ is asymptotic to one in Σ . So we draw phase portraits on Σ . Here carrying simplex Σ is homeomorphic to $\{y \in \mathbb{R}_+^3 : \sum_i y_i = 1\}$.

- Φ^0 always possesses

(1) *equilibria*: $O(0, 0, 0)$;

(2) *three axial equilibria*: $R_1(1, 0, 0)$, $R_2(0, 1, 0)$, $R_3(0, 0, 1)$;

(3) *the unique positive equilibrium*: $P = \frac{1}{1+\beta+\gamma}(1, 1, 1)$;

(4) *possible planar equilibria*: $R_{12} = \frac{1}{1-\beta\gamma}(1-\beta, 1-\gamma, 0)$,
 $R_{23} = \frac{1}{1-\beta\gamma}(0, 1-\beta, 1-\gamma)$, $R_{31} = \frac{1}{1-\beta\gamma}(1-\gamma, 0, 1-\beta)$.

Table: The classification for the flow Φ^0 on Σ

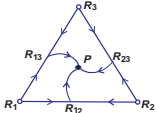
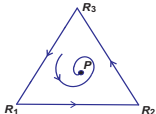
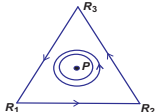
Parameter conditions	Equilibria	Phase Portrait
a: $0 < \beta, \gamma < 1$	$O, R_1, R_2, R_3, R_{12}, R_{13}, R_{23}, P$	
b: (i) $\beta + \gamma < 2$ (ii) $\beta \geq 1, \gamma < 1$ or $\gamma \geq 1, \beta < 1$	O, R_1, R_2, R_3, P	
c: (i) $\beta + \gamma = 2$ (ii) $\beta, \gamma \neq 1$	O, R_1, R_2, R_3, P	

Table: continued

Parameter conditions	Equilibria	Phase Portrait
(i) $\beta + \gamma > 2$ d: (ii) $\gamma > 1, \beta \leq 1$ or $\gamma \leq 1, \beta > 1$	O, R_1, R_2, R_3, P	
e: $\beta, \gamma > 1$	$O, R_1, R_2, R_3, R_{12}, R_{13}, R_{23}, P$	
f: $\beta = \gamma = 1$	$\forall x \in \Sigma \cup \{O\}$	

Complete Depiction

Theorem 15 (Chen, Dong, Jiang, Niu and Zhai)

- (i) For any equilibrium $Q \in \mathcal{E}$, $\mu_Q^\epsilon(\cdot) \xrightarrow{w} \delta_Q(\cdot)$ as $\epsilon \rightarrow 0$, which is valid to the cases a, b, e, f.
- (ii) For the case c, ν_h^ϵ converges weakly to the Haar measure on the closed orbit $\Gamma(h)$ as $\epsilon \rightarrow 0, 0 < h \leq \frac{1}{27}$.
- (iii) For the case d, if $\mu^i := \nu_y^{\epsilon^i} \in \mathcal{M}_S(\epsilon_0)$, $i = 1, 2, \dots$, satisfying $\epsilon^i \rightarrow 0$ and $\mu^i \xrightarrow{w} \mu$ as $i \rightarrow \infty$, then $\mu(\{R_1, R_2, R_3\}) = 1$.

Conclusions

♠ The Bernoulli Lemniscate Example shows that the Birkhoff center consists of the origin O (saddle point) and strongly unstable spirals $\{P^+, P^-\}$. Relatively, the O is **more stable** than $\{P^+, P^-\}$.

All weak limits support at the O under the diffusion matrix is nondegenerate.

- **The most unstable positions** for the deterministic system may be recognised by the added small stochastic term.

♠ The May-Leonard Example in **case d** indicates that the Birkhoff center of Φ^0 on $\Sigma = \{y \in \mathbb{R}_+^3 : \sum_i y_i = 1\}$ is composed of P (which is strongly repelling on Σ) and three saddles $\{R_1, R_2, R_3\}$ (which are **relatively more stable** than P).

The weak limits are more complex, but keep the original deterministic classification.

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Thank you!