

Mean Field Optimal Control Formulation for Global Optimization

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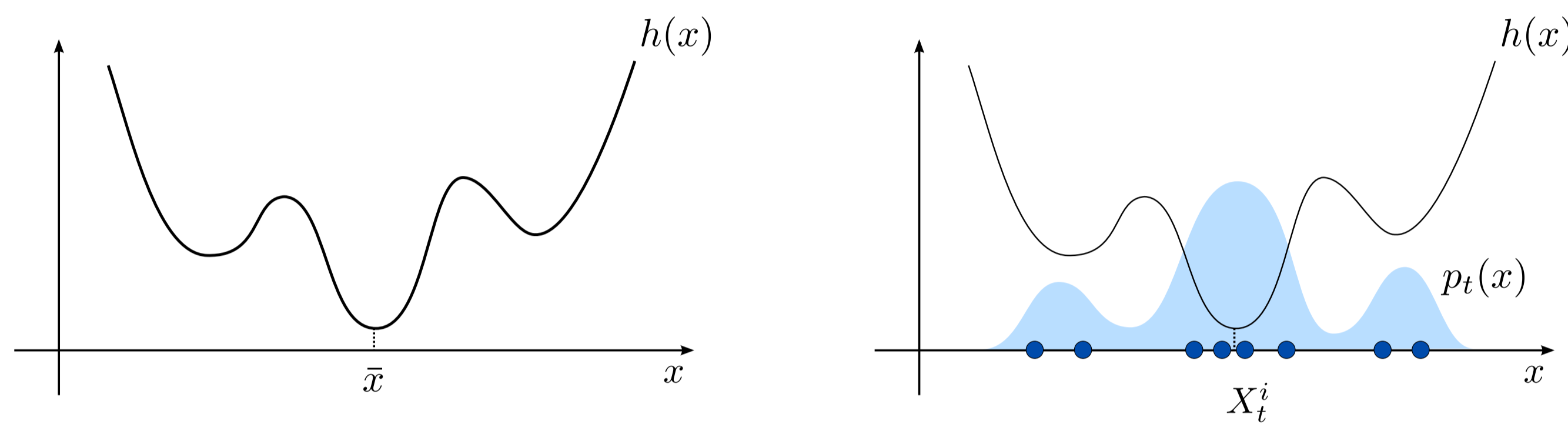
Global Optimization

Problem:

$$\min_{x \in \mathbb{R}^d} h(x)$$

► $h : \mathbb{R}^d \rightarrow \mathbb{R}$

► $\bar{x} := \arg \min_x h(x)$



Controlled Particle Filter Approach

Bayesian model:

$$p_t^*(x) = \frac{p_0^*(x) e^{-th(x)}}{\int p_0^*(y) e^{-th(y)} dy} \rightarrow \delta_{\bar{x}}, \quad \text{as } t \rightarrow \infty$$

Standard algorithm: Importance sampling and resampling [Wang, et. al. WSC (2010)]

Control-based algorithm: (Inspired by Feedback Particle Filter [Yang, et. al. TAC (2013)])

$$\text{ODE: } \frac{dX_t^i}{dt} = -\nabla \phi_t(X_t^i), \quad X_0^i \sim p_0^*$$

$$\text{PDE: } -\frac{1}{\rho_t(x)} \nabla \cdot (\rho_t(x) \nabla \phi_t(x)) = h(x) - \hat{h}_t$$

► $\{X_t^i\}_{i=1}^N \in \mathbb{R}^d$ is the state of the i^{th} particle

► ρ_t is the density of X_t^i

► $\hat{h}_t := \int h(x) \rho_t(x) dx$

Consistency: The density ρ_t of X_t^i is equal to the Bayesian density

$$\rho_t = p_t^*$$

Objective of this work

Derive an optimal control formulation for the algorithm

Related work: Brockett, AMS/IP Stud. Adv. Math. (2007), Huang, et. al. TAC (2007), Bensoussan et. al. IJPAM (2015), Chen, et. al. TAC (2016)

Optimal control formulation

Problem:

$$\text{Minimize: } J(u) := \int_0^T \underbrace{L(\rho_t, u_t)}_{\text{Lagrangian}} dt + \underbrace{\int h(x) \rho_T(x) dx}_{\text{terminal cost}}$$

$$\text{Constraint: } \frac{\partial \rho_t}{\partial t} + \nabla \cdot (\rho_t u_t) = 0, \quad \rho_0(x) = p_0^*(x)$$

where

$$L(\rho, u) = \int_{\mathbb{R}^d} \left[\frac{1}{2} \left| \frac{1}{\rho(x)} \nabla \cdot (\rho(x) u(x)) \right|^2 + \frac{1}{2} |h(x) - \hat{h}|^2 \right] \rho(x) dx$$

Dynamic Programming

Define

$$\text{Value function: } V(\rho, t) := \inf_u \left[\int_t^T L(\rho_s, u_s) ds + \int h(x) \rho_T(x) dx \right]$$

$$\text{Hamiltonian: } H(\rho, q, u) := L(\rho, u) - \int_{\mathbb{R}^d} q(x) \nabla \cdot (\rho(x) u(x)) dx$$

then

$$\frac{\partial V}{\partial t}(\rho, t) + \inf_u H(\rho, \frac{\partial V}{\partial \rho}(\rho, t), u) = 0,$$

$$V(\rho, T) = \int h(x) \rho(x) dx$$

Solution to the DP equation

► The value function is

$$V(\rho, t) = \int h(x) \rho(x) dx$$

$$\frac{\partial V}{\partial \rho}(\rho, t) = h$$

► The optimal control solves the pde

$$\frac{1}{\rho(x)} \nabla \cdot (\rho(x) u(x)) = h(x) - \hat{h}, \quad \forall x \in \mathbb{R}^d$$

Hamilton's equations

$$\frac{dX_t^i}{dt} = u_t(X_t^i), \quad X_0^i \sim p_0^*$$

$$u_t = \arg \min_{\nu} H(\rho_t, h, \nu)$$

Quadratic Gaussian case

ρ_0^* is Gaussian $N(m_0, \Sigma_0)$

$$h(x) = \frac{1}{2} (x - \bar{x})^T H (x - \bar{x})$$

then

ρ_t is Gaussian $N(m_t, \Sigma_t)$

$$u(x) = \underbrace{-K_t(x - m_t) - b_t}_{\text{Affine control law}}$$

where

$$b_t = \int_{\mathbb{R}^d} x (h(x) - \hat{h}_t) \rho_t(x) dx$$

$$K_t \Sigma_t + \Sigma_t K_t = \int_{\mathbb{R}^d} (x - m)(x - m)^T (h(x) - \hat{h}_t) \rho_t(x) dx$$

Affine approximation of the control law

Particle filter:

$$\frac{dX_t^i}{dt} = -K_t^{(N)} (X_t^i - m_t^{(N)}) - b_t^{(N)}$$

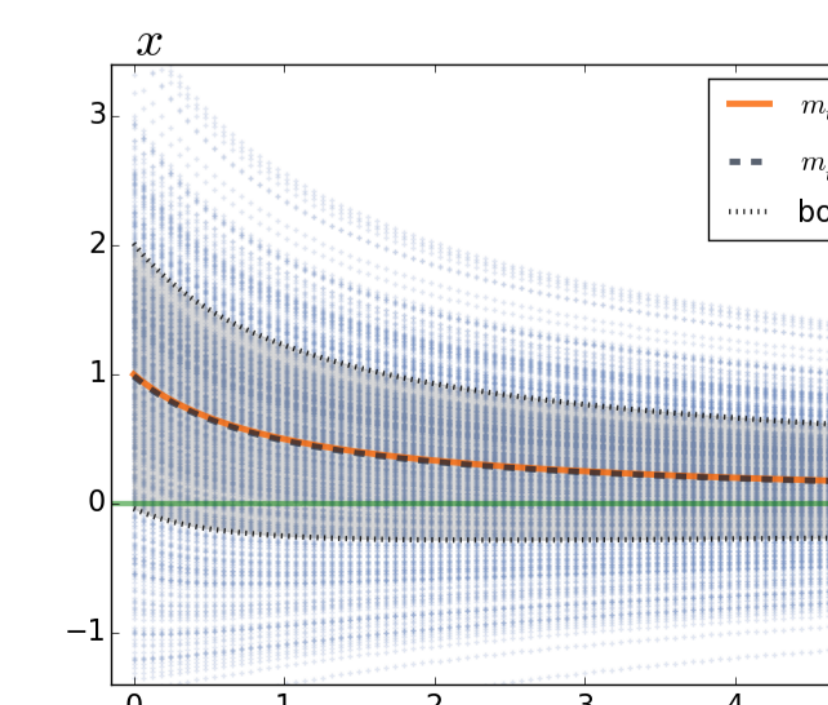
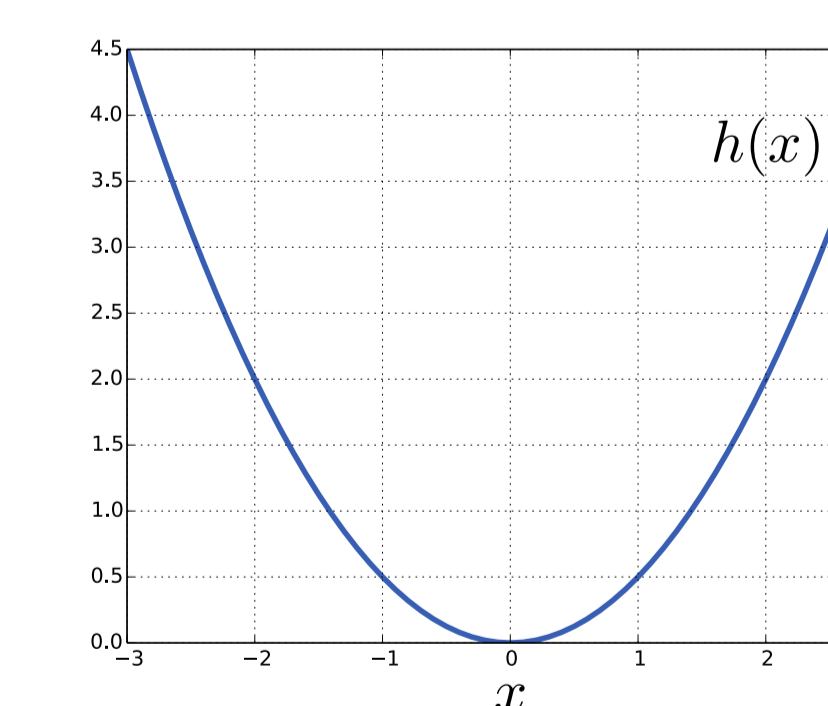
where $(m_t^{(N)}, \Sigma_t^{(N)})$ is the empirical mean and variance and

$$b_t^{(N)} = \frac{1}{N} \sum_{i=1}^N X_t^i (h(X_t^i) - \hat{h}_t^{(N)})$$

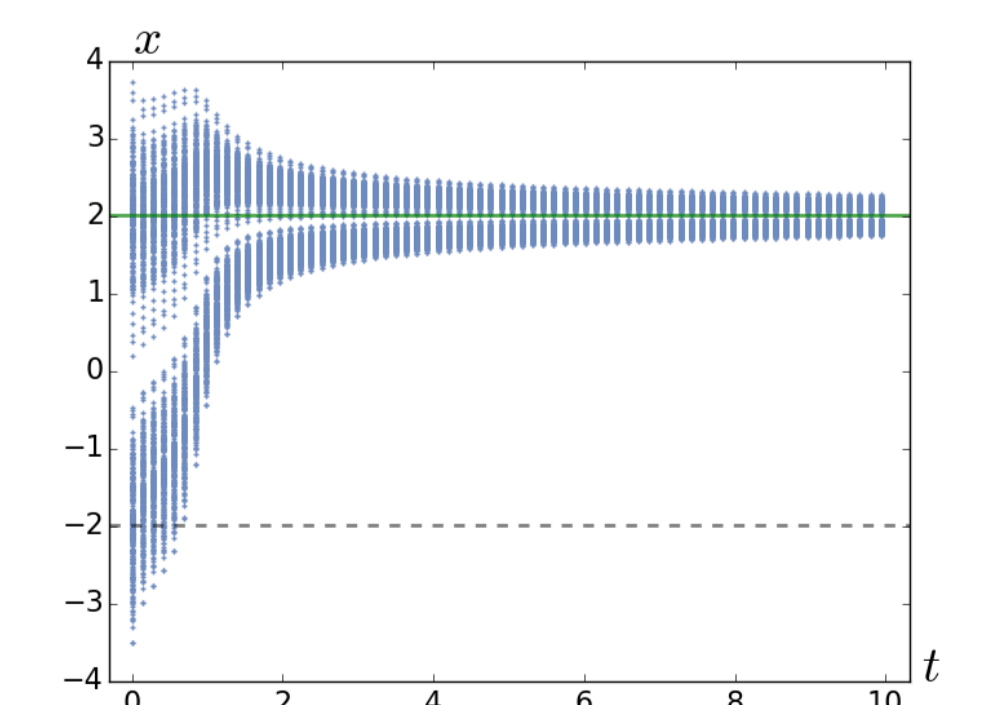
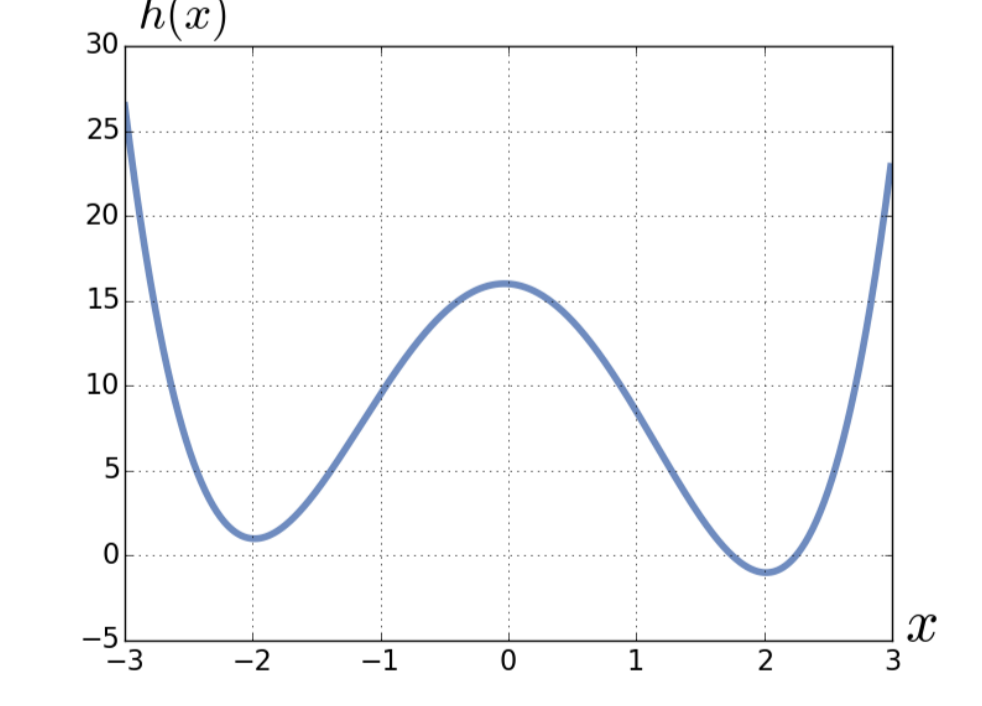
$$K_t^{(N)} \Sigma_t^{(N)} + \Sigma_t^{(N)} K_t^{(N)} = \frac{1}{N} \sum_{i=1}^N (X_t^i - m_t^{(N)}) (X_t^i - m_t^{(N)})^T (h(X_t^i) - \hat{h}_t^{(N)})$$

Numerical simulation

Quadratic function



Double-well function



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