

# Stability and uniform propagation of chaos prop. of Ensemble Kalman-Bucy filters

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INRIA & UNSW Maths/Stats

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**Synthesis  $\subset$  joint works, hyperref. (2016-2017):**

- ▶ AoAP-17 (Unif. EnKBF)+ J. Tugaut.
- ▶ SIAM C. & Opt. (Unif. En-EKBF)+ A. Kurtzmann, J. Tugaut.
- ▶ Arxiv 1 (Stability KBF)+ **A.N. Bishop**
- ▶ Arxiv 2 (Stability EKBF)+ A. Kurtzmann, J. Tugaut.
- ▶ Arxiv 3 (Perturbation KB)+ **A.N. Bishop, S. Pathiraja.**
- ▶ (Working paper CLT/Bias/Taylor)+ **A.N. Bishop + A. Niclas**

Kalman-Bucy filter

A McKean-Vlasov interpretation

Mean field/Ensemble Kalman-Bucy filter

Stability of Kalman-Bucy diffusions

- Stability of Riccati semigroup

- Stability of stochastic flows

Propagation of chaos estimates

- Some observations/numerical issues

- "Technical" problems

- Some uniform estimates

Nonlinear models

- Extended Kalman-Bucy-filters

- Extended Ensemble Kalman-Bucy-filters

- A stability theorem

- Uniform propagation of chaos estimates

## Kalman-Bucy filter

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# Kalman-Bucy filter

## Linear+Gaussian filtering problem

$$\begin{cases} dX_t = A X_t dt + R^{1/2} dW_t \\ dY_t = C X_t dt + \Sigma^{1/2} dV_t \end{cases} \rightsquigarrow \mathcal{F}_t := \sigma(Y_s, s \leq t).$$

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## Optimal $\mathbb{L}_2$ -filter = Kalman-Bucy filter

$$\hat{X}_t := \mathbb{E}(X_t | \mathcal{F}_t) \quad \text{and} \quad P_t := \mathbb{E}((X_t - \mathbb{E}(X_t | \mathcal{F}_t))(X_t - \mathbb{E}(X_t | \mathcal{F}_t))')$$

$\Downarrow$

$$d\hat{X}_t = A \hat{X}_t dt + P_t C' \Sigma^{-1} (dY_t - C \hat{X}_t dt)$$

## with the Riccati equation

$$\partial_t P_t = \text{Ricc}(P_t) := AP_t + P_t A' - P_t S P_t + R \quad \text{with} \quad S := C' \Sigma C$$

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# Nonlinear Kalman-Bucy diffusion

## Reformulation

$$\text{Law}(X_t \mid \mathcal{F}_t) = \mathcal{N} \left[ \widehat{X}_t, P_t \right] = \text{Law}(\overline{X}_t \mid \mathcal{F}_t) = \eta_t$$

## in terms of the McKean-Vlasov type diffusion

$$d\overline{X}_t = A \overline{X}_t dt + R^{1/2} d\overline{W}_t + \mathcal{P}_{\eta_t} C' \Sigma^{-1} \left[ dY_t - \left( C \overline{X}_t dt + \Sigma^{1/2} d\overline{V}_t \right) \right]$$

with the covariance matrices

$$\mathcal{P}_{\eta_t} = \eta_t \left[ (e - \eta_t(e))(e - \eta_t(e))' \right] \quad \text{with} \quad e(x) := x.$$

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# The Ensemble Kalman-Bucy filter

**Mean field interpretation**  $\rightsquigarrow$   $N + 1$  interacting diffusions

$$d\xi_t^i = A \xi_t^i dt + R^{1/2} d\bar{W}_t^i + p_t C' \Sigma^{-1} \left[ dY_t - \left( C \xi_t^i dt + \Sigma^{1/2} d\bar{V}_t^i \right) \right]$$

**with the rescaled particle covariance matrices**

$$p_t := \left( 1 + \frac{1}{N} \right) \mathcal{P}_{\eta_t^N} = \frac{1}{N} \sum_{1 \leq i \leq N+1} (\xi_t^i - m_t) (\xi_t^i - m_t)'$$

**and the empirical measures**

$$\eta_t^N := \frac{1}{N+1} \sum_{1 \leq i \leq N+1} \delta_{\xi_t^i} \quad \text{and the sample mean} \quad m_t := \frac{1}{N+1} \sum_{1 \leq i \leq N+1} \xi_t^i.$$

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*where is the Riccati equation?*

# Th1: The EnKF equations

## The EnKF equation

$$dm_t = A m_t dt + p_t C' \Sigma^{-1} (dY_t - C m_t dt) + \frac{1}{\sqrt{N+1}} d\bar{M}_t$$

with an  $r_1$ -dimensional martingale  $\bar{M}_t = (\bar{M}_t(k))_{1 \leq k \leq r_1}$  with angle-brackets

$$\partial_t \langle \bar{M} | \otimes | \bar{M} \rangle_t = R + p_t S p_t.$$

## The particle/ensemble Riccati equation

$$dp_t = \text{Ricc}(p_t) dt + \frac{1}{\sqrt{N}} dM_t$$

Symmetric matrix-valued martingale  $M_t = (M_t(k, l))_{1 \leq k, l \leq r_1}$

Angle brackets given by the Wick-type formula

$$\partial_t \langle M | \otimes | M \rangle_t^\# = p_t \otimes_{\text{sym}} (R + p_t S p_t)$$

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Orthogonality property

$$\forall 1 \leq k, l, l' \leq r_1 \quad \langle M(k, l), \overline{M}(l') \rangle_t = 0.$$

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## (H) Observability + Controllability

Observe that

$$d\bar{X}_t = (\mathbf{A} - \mathbf{P}_t\mathbf{S}) \bar{X}_t dt + R^{1/2} d\bar{W}_t + P_t C' \Sigma^{-1} \left[ dY_t - \Sigma^{1/2} d\bar{V}_t \right]$$

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↓

**Steady state:  $\exists P > 0$  such that  $\text{Ric}(P) = 0$  and**

$$\zeta(\mathbf{A} - \mathbf{P}\mathbf{S}) := \max \{ \text{Re}(\lambda) : \lambda \in \text{Spec}(\mathbf{A} - \mathbf{P}\mathbf{S}) \} < 0$$

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⇓

**Steady state diffusion**

$$d\bar{X}_t \simeq (\mathbf{A} - \mathbf{P}\mathbf{S}) \bar{X}_t dt + R^{1/2} d\bar{W}_t + PC' \Sigma^{-1} \left[ dY_t - \Sigma^{1/2} d\bar{V}_t \right]$$

**STABLE EVEN WHEN  $A$  is unstable.**

# (H) Observability + Controllability

## Controllability & Observability Gramians

$$C_t := \int_0^t e^{sA} R e^{sA'} ds \quad O_t := \int_0^t e^{-sA'} S e^{-sA} ds$$

$$O_t(C) := C_t^{-1} \left[ \int_0^t e^{(t-s)A} C_s S C_s e^{(t-s)A'} ds \right] C_t^{-1}$$

$$C_t(O) := O_t^{-1} \left[ \int_0^t e^{-(t-s)A'} O_s R O_s e^{-(t-s)A} ds \right] O_t^{-1}$$

⇓

⇒ ∃  $v > 0$  (a.k.a obs-control interval) ∃  $\varpi_{\pm}^{o,c}, \varpi_{\pm}^c(O), \varpi_{\pm}^o(C) > 0$  s.t.

$\varpi_-^c Id \leq C_v \leq \varpi_+^c Id$  and so on, for the other Gramians.

## Bucy's theorems

**Notation**  $\mathcal{E}_{s,t} = \exp \left[ \int_s^t Q_u du \right] =$  state transition matrix

$$\partial_s \mathcal{E}_{s,t} = -\mathcal{E}_{s,t} Q_s \quad \text{and} \quad \partial_t \mathcal{E}_{s,t} = Q_t \mathcal{E}_{s,t}$$

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**Theo 1 [Bucy]**  $\forall (t, P_0)$

$$(\mathcal{O}_v(\mathcal{C}) + \mathcal{C}_v^{-1})^{-1} \leq P_{t+v} \leq \mathcal{O}_v^{-1} + \mathcal{C}_v(\mathcal{O})$$

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**Theo 2 [Bucy]**

$\exists \alpha, \beta > 0$  that depends on  $\varpi_{\pm}^{o,c}, \varpi_{\pm}^c(\mathcal{O}), \varpi_{\pm}^o(\mathcal{C})$  s.t.  $\forall t \geq s \geq v$

$$\| \exp \oint_s^t (A - P_u S) du \|_2^2 \leq \alpha \exp \{ -\beta(t - s) \}$$

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*Also true for any  $t \geq s \geq 0$  with  $\alpha$  depending on  $P_0$ .*



## Some consequences

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**Theo**  $\exists \nu > 0$  s.t. for any  $t \geq s \geq 0$ ,  $x_1, x_2 \in \mathbb{R}^n$ ,  $Q_1, Q_2 \geq 0$ ,  $n \geq 2$

$$\begin{aligned} & \mathbb{E} (\|\psi_{s,t}(x_1, Q_1) - \psi_{s,t}(x_2, Q_2)\|_2^n \mid \mathcal{X}_s)^{1/n} \\ & \leq c_{Q_1, Q_2} e^{-\nu(t-s)} [\|x_1 - x_2\|_2 + \{\|x_2 - X_s\|_2 + \sqrt{n}\} \|Q_1 - Q_2\|_2] \end{aligned}$$

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*Any choice*

$$\nu \in \{ \beta, (1 - \epsilon) \varsigma(A - PS), \lambda_{\max}((A - PS)_{\text{sym}}) \}$$

*is fine but  $c_{Q_1, Q_2}$  maybe larger than you expect.*

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## Back to the EnKF - Some observations/numerical issues

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  - ▶  $\text{rank}(p_t) \leq N < r_1 \Rightarrow (r_1 - N)$  state dimensions not driven by  $Y_t$ .
  - ▶  $r_1 = 1 \Rightarrow p_t$  has an heavy tailed invariant distribution  $\propto x^{-(N+3)}$
- $\implies \forall \epsilon > 0 \quad \mathbb{E}(e^{\epsilon q_t}) = \infty \quad \text{and} \quad \forall m \geq N+2 \quad \mathbb{E}(q_t^m) = \infty$

$\rightsquigarrow$  **Moment explosions**



# Back to the EnKF

**We really need a stable signal (for uniform estimates)**



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*Spectral abscissa*  $\rightsquigarrow$  constants (conditioning numbers) depending on diagonalisation basis. *Complicated analysis when*  $A \rightsquigarrow A - p_t S$ .

"Technical" problems even when  $\mu(A) < 0$

$\bar{A} := A - PS$  stable matrices  $\not\Rightarrow \bar{a} = A - \rho S$  stable matrices

$$\rho = P + N^{-1/2} \Sigma \quad \Longrightarrow \quad \bar{a} = \bar{A} + N^{-1/2} \Sigma S$$

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**BUT:**

$$H(AS) \quad S = s Id \quad \text{and} \quad \mu(A) < 0$$

$$\Longrightarrow \forall p \quad \mu(A - pS) \leq \mu(A) + s \mu(-p) < \mu(A) < 0$$

$$\Longrightarrow p_t \text{ never hits the divergence set } \{\Sigma : \varsigma(\bar{A} + \Sigma S) > 0\}$$

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**More generally  $(A - pS)$  may be locally ill-conditioned in the sense that**

$$\exists Q : \mu(A - QS) = \lambda_{\max}((A - QS)_{\text{sym}}) > 0 > \lambda_{\min}((A - QS)_{\text{sym}})$$

# Under $H(AS)$

**Theo**  $\forall n \geq 1 \exists N_n \geq 1$

$$\sup_{N \geq N_n} \sup_{t \geq 0} \sqrt{N} \mathbb{E} [\|p_t - P_t\|_F^n] \vee \sup_{N \geq N_n} \sup_{t \geq 0} \sqrt{N} \mathbb{E} [\|\xi_t^1 - \bar{X}_t\|^n] < \infty$$

$\Downarrow$

**Cor**  $\forall n \geq 1 \exists N_n \geq 1$

$$\sup_{N \geq N_n} \sup_{t \geq 0} \sqrt{N} \mathbb{W}_n (\text{Law}(\xi_t^1), \eta_t) \vee \sup_{N \geq N_n} \sup_{t \geq 0} \sqrt{N} \mathbb{E} (|\eta_t^N(f) - \eta_t(f)|^n) < \infty$$

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# Nonlinear models

## Extended Kalman-Bucy-filters

$$d\hat{X}_t = A(\hat{X}_t) dt + P_t C' \Sigma^{-1} [dY_t - C\hat{X}_t dt]$$

with the "stochastic" Riccati equation:

$$\partial_t P_t = \partial A(\hat{X}_t) P_t + P_t \partial A(\hat{X}_t)' + R - P_t S P_t$$

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## McKean-Vlasov interpretation

$$\begin{aligned} d\bar{X}_t = & \mathcal{A}(\bar{X}_t, \mathbb{E}[\bar{X}_t | \mathcal{G}_t]) dt + R^{1/2} d\bar{W}_t \\ & + \mathcal{P}_{\eta_t} C' R_2^{-1} [dY_t - (C\bar{X}_t dt + \Sigma^{1/2} d\bar{V}_t)] \end{aligned}$$

with the drift function

$$\mathcal{A}(x, m) := A[m] + \partial A[m] (x - m).$$

# Extended Ensemble Kalman-Bucy-filters

## En-EKF = Mean field particle model

$$d\xi_t^i = \mathcal{A}(\xi_t^i, m_t) dt + R^{1/2} d\bar{W}_t^i \\ + p_t C' \Sigma^{-1} \left[ dY_t - \left( C \xi_t^i dt + \Sigma^{1/2} d\bar{V}_t^i \right) \right]$$

with the sample means  $m_t$  and covariance matrices  $p_t$  and the drift

$$\mathcal{A}(\xi_t^i, m_t) := A[m_t] + \underbrace{\frac{\partial A[m_t]}{\partial m_t} (\xi_t^i - m_t)}_{\text{Repulsion/Attraction w.r.t. } m_t}$$

# Some illustrations

## Langevin type signal processes

$$R = \sigma^2 Id \quad \text{and} \quad (A, \partial A) = (-\partial\mathcal{V}, -\partial^2\mathcal{V})$$

## Non quadratic potential ( $q \in \mathbb{R}^r, Q_1, Q_2 \geq 0$ )

$$\mathcal{V}(x) = \frac{1}{2} \langle Q_1 x, x \rangle + \langle q, x \rangle + \frac{1}{3} \langle Q_2 x, x \rangle^{3/2}$$

## Interacting diffusion gradient flows

$$\mathcal{V}(x) = \sum_{1 \leq i \leq r} \mathcal{U}_1(x_i) + \sum_{1 \leq i \neq j \leq r} \mathcal{U}_2(x_i, x_j)$$

for some convex confining potential  $\mathcal{U}_i : \mathbb{R}^i \mapsto [0, \infty[$

# Regularity conditions

**Full observation  $S = s Id$  and**

$$-\lambda_{\partial A} := \sup_{x \in \mathbb{R}^d} \lambda_{\max}(\partial A(x) + \partial A(x)') < 0$$

$$\|\partial A(x) - \partial A(y)\| \leq \kappa_{\partial A} \|x - y\|$$

**Examples: Langevin signal-diffusion**

$$(\lambda_{\partial A}, \kappa_{\partial A}) = \beta \left( 2^{-1} \lambda_{\min}(Q_1), 2 \lambda_{\max}^{3/2}(Q_2) \right).$$

*more generally  $\partial^2 \mathcal{V} \geq \nu Id \oplus$  Lipschitz condition*

# Stability theorem

$(\bar{X}_t, \bar{Z}_t) :=$  McKean-Vlasov starting at  $(\bar{X}_0, \bar{Z}_0)$

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**Theo** [+Kurtzmann-Tugaut]

When  $\lambda_{\partial A}$  is sufficiently large we have

$$\mathbb{W}_2(\text{Law}(\bar{X}_t), \text{Law}(\bar{Z}_t)) \leq c \exp[-t \lambda] \quad \text{for some } \lambda > 0.$$

$\exists$  *more explicit description in terms of*  $(R, S, \kappa_{\partial A})$ .

# Propagation of chaos

$$\mathbb{P}_t^N := \text{Law}(m_t, p_t) \quad \mathbb{P}_t := \text{Law}(\widehat{X}_t, P_t)$$

and

$$\mathbb{Q}_t^N := \text{Law}(\xi_t^1) \quad \mathbb{Q}_t := \text{Law}(\overline{X}_t)$$



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**Theo** [+Kurtzmann-Tugaut]

When  $\lambda_{\partial A}$  is sufficiently large,  $\exists \beta \in ]0, 1/2]$  s.t.

$$\sup_{t \geq 0} \mathbb{W}_2(\mathbb{P}_t^N, \mathbb{P}_t) \vee \sup_{t \geq 0} \mathbb{W}_2(\mathbb{Q}_t^N, \mathbb{Q}_t) \leq c N^{-\beta}$$

as soon as  $\text{tr}(P_0)$  is not too large and  $N$  large enough...