# Estimation of pattern formation in stochastic reaction-diffusion systems with the Block Particle Filter

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# **Non-linear Filtering**

 $\diamond$  Assume X to be a Markov chain with underlying probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , where  $X : \mathbb{N} \times \Omega \ni (k, \omega) \mapsto X_k(\omega) \in \mathbb{R}^{N_x}$ .

 $\diamond$  Consider a sequence of observations  $(y_k)_{k\in\mathbb{N}}.$ 

PROBLEM: Estimate the stochastic process  $\pi = (\pi_k)_{k \in \mathbb{N}}$ , where  $\pi_k(\mathcal{A}) = \mathbb{P}(X_k \in \mathcal{A} | Y_{i:k} = y_{i:k})$  for all  $\mathcal{A} \in \mathcal{B}(\mathbb{R}^{N_x})$ .

The filters  $\pi_k$  can be computed recursively via

 $\pi_{k-1} \xrightarrow{\text{prediction}} \widetilde{\pi}_k = \mathcal{P}_k \pi_{k-1} \xrightarrow{\text{correction}} \pi_k = \mathcal{C}_k \widetilde{\pi}_k, \tag{1}$ 

with operators  $P_k$  and  $C_k$  satisfying

# This work

optimal choice (optimal. SIR, minimal MSE)  $q_k(x) = \frac{p(y_k | y_{\text{I:}k-\text{I}}, x_{\text{o:}k-\text{I}}, x) p(x | x_{k-\text{I}})}{p(y_k | y_{\text{I:}k-\text{I}}, x_{\text{o:}k-\text{I}})};$ 



$$(\mathbf{P}_k \boldsymbol{\pi}_{k-\mathbf{I}})(\boldsymbol{\mathcal{A}}) \stackrel{\Delta}{=} \int \mathbf{P}_k(\boldsymbol{x}, \boldsymbol{\mathcal{A}}) \boldsymbol{\pi}_{k-\mathbf{I}}(d\boldsymbol{x}), \quad (\mathbf{C}_k \widetilde{\boldsymbol{\pi}}_k)(\boldsymbol{\mathcal{A}}) \stackrel{\Delta}{=} \frac{\int_{\boldsymbol{\mathcal{A}}} \mathbf{C}_k(\boldsymbol{x}) \widetilde{\boldsymbol{\pi}}_k(d\boldsymbol{x})}{\widetilde{\boldsymbol{\pi}}_k(\mathbf{C}_k)}.$$

Classical particle filters:

Let particles  $\{X_k^{(n)}\}_{n=1}^{N_p}$  be  $N_p$  mutually independent stochastic processes, with common distribution  $\pi_k$  with density  $p_k$ . Let  $\pi^{N_p}$  be the sequence of empirical distributions

$$\pi_k^{N_p} \stackrel{\Delta}{=} rac{\mathrm{I}}{N_p} \sum_{n=\mathrm{I}}^{N_p} \delta_{X_k^{(n)}}, \quad X_k^{(n)} \sim p_k.$$

Since  $p_k$  is unavailable, we sample  $\{X_k^{(n)}\}_{n=1}^{N_p}$  from importance distributions with density  $q_k$  instead (normalised Importance Sampling), resulting in

$$rac{1}{N_p} \sum_{n=1}^{N_p} w_k(X_k^{(n)}) \delta_{X_k^{(n)}}, \qquad w_k(x) = rac{p_k(x)}{q_k(x)}, \qquad X_k^{(n)} \sim q_k,$$

with the support of  $q_k$  containing the support of  $p_k$ .

Once  $q_k$  is chosen, procedure (1) is approximated via

 $\pi_{k-\mathbf{I}}^{N_p} \xrightarrow{\text{prediction/sampling}} \widetilde{\pi}_k^{N_p} = \mathbf{P}_k \pi_{k-\mathbf{I}}^{N_p} \xrightarrow{\text{correction}} \pi_k^{N_p} = \mathbf{C}_k \widetilde{\pi}_k^{N_p}.$ 

#### Block particle filtering [1]:

 $X_k$ 

State

To address the curse of dimensionality, we assume that the dynamics and observations at a spatial location depend only on state-variables associated with its neighbourhood. ♦ We reconstruct the concentrations of chemical substances in a reactive-diffusion system using noisy spectral observations.

Figure 1: An oscillatory chemical reaction propagating across a petri dish.

### **Case-study: The Oregonator System [2]**

A reaction-diffusion system with  $\diamond$  a quasi-two-dimensional space  $U = \{u \in \mathbb{R}^2 : \mathbf{o} \le u_i < \overline{U}, i \in \{\mathbf{I}, \mathbf{2}\}\}$  (e.g. a petri dish);  $\diamond$  sets of chemical species  $S = \{S_1, \dots, S_6\}$  distributed over U

 $\diamond$  dynamics of  $z^{(v)}(t) = z((v_1, v_2)\Delta u, t)$  approximated as

 $dz^{(v)} = \left[ (\overline{S} - \underline{S})^{\mathsf{T}} v (z^{(v)}) + D_z \nabla^2 z^{(v)} \right] dt, \quad \forall v \in V,$ 

with stoichiometric matrix  $\underline{S} \in \mathbb{N}^{5 \times 5}$  for the reactants and  $\overline{S} \in \mathbb{N}^{5 \times 5}$  for the products;  $\diamond$  environmental perturbations added in the form of Brownian Motion  $B^z$  $dz(u, t) = f_z(z(u, t), \nabla^2 z(u, t)) dt + g_z(z(u, t)) dB_t^z;$ 

 $\diamond$  an output equation of the form  $y^{(v)}(t) = H_z z^{(v)}(t) + e_z(t)$ , with  $y^{(v)}(t) = y((v_1, v_2)\Delta u, t)$ . For this reaction network,

 $([\mathcal{S}_4], [\mathcal{S}_5], [\mathcal{S}_6] = \text{ constant }) \land ([\mathcal{S}_3] \text{ slowly varying}) \xrightarrow{[3]} z^{(v)}(t) \in \mathbb{R}^2, H_z \in \mathbb{R}^{10 \times 2}.$ 

Once  $q_k$  is chosen, procedure (1) is instead approximated via

$$\pi_{k-\mathbf{I}}^{N_p} \xrightarrow{\text{prediction/sampling}} \widetilde{\pi}_k = \mathbf{P}_k \pi_{k-\mathbf{I}}^{N_p} \xrightarrow{\text{blocking/correction}} \pi_k^{N_p} = \mathbf{C}_k \mathbf{B} \widetilde{\pi}_k^{N_p},$$

where the operator B is built in the following way:

 $\begin{array}{l} \diamond(X_k,Y_k) \text{ is a random field } (X_k,Y_k)_{v\in V} \text{ indexed by a (finite) undirected graph } \mathcal{G} = (V,W); \\ \diamond \text{ Graph } \mathcal{G} \text{ has vertex set } V = \{v\in\mathbb{N}^2: \mathbf{I}\leq v_i\leq\overline{V}, i\in\{\mathbf{I},\mathbf{2}\}, \overline{V}\in\mathbb{N}\}; \\ \diamond \text{ Vertices of } \mathcal{G} \text{ can be partitioned in } V = \bigcup_{V_b\in\mathcal{K}}V_b, V_b\cap V_{b'} = \emptyset \text{ for } V_b\neq V_{b'}, V_b, V_{b'}\in\mathcal{K}; \\ \diamond \mathcal{K} \text{ is a collection of non-overlapping blocks } \{(v_{\mathsf{o}}+\{\mathbf{I},\ldots,\overline{V}_b\}^2)\cap V:v_{\mathsf{o}}\in\overline{V}_b\mathbb{N}^2\}. \end{array}$ 

$$\mathbf{B}\boldsymbol{\pi}_k \coloneqq \bigotimes_{V_b \in \mathcal{K}} \mathbf{B}^{V_b} \boldsymbol{\pi}_k, \text{ where } \mathbf{B}^{V_b} \boldsymbol{\pi}_k \text{ is the marginal distribution of } \boldsymbol{\pi}_k \text{ on } \prod_{v \in V_b} \mathbb{R}^{N_x^{(v)}}.$$

We let 
$$X_k = (z^{(v_1, v_2)}(t_k))_{v_1, v_2=1}^V$$
 and  $Y_k = (y^{(v_1, v_2)}(t_k))_{v_1, v_2=1}^V$ .  
 $\left((\overline{V}/\overline{V_b})^2 = 400\right) \wedge \left(\text{block size } \overline{V_b} = 5\right) \longrightarrow X_k \in \mathbb{R}^{2 \cdot (100)^2}, Y_k \in \mathbb{R}^{10 \cdot (100)^2}.$ 

# References

 [1] Patrick Rebeschini and Ramon van Handel. Can local particle filters beat the curse of dimensionality? The Annals of Applied Probability, 25(5):2809 – 2866, 2015.

[2] Richard J. Field and Richard M. Noyes. Oscillations in chemical systems. iv. limit cycle behavior in a model of a real chemical reaction. Journal of Chemical Physics, 60:1877–1884, 1974.

[3] James P. Keener and John J. Tyson. Spiral waves in the belousov-zhabotinskii reaction. Physica D: Nonlinear Phenomena, 21(2):307–324, 1986.





Figure 2: Snapshots of  $(X_k)_1$  (4 first columns) and  $(X_k)_2$  (4 last columns) for the Oregonator model at different times  $t_k$ . First row shows a draw for  $X_k$  used to generate observation  $y_k$ . We estimated  $\hat{X}_k$  with the Block Particle Filter (for each block  $N_p = 128$  particles) with a standard (2nd row) and with an optimal (3rd row) choice of importance densities  $q_k$ .  $[f_z]_1 = a^{-1}(z_1(1-z_1) - \frac{bz_2(z_1-c)}{z_1+c}) + D_{z_1}\nabla^2 z_1$ ,  $[f_z]_2 = (z_1 - z_2) + D_{z_2}\nabla^2 z_2$ , with constants (a, b, c) = (0.08, 0.95, 0.0075),  $(D_{z_1}, D_{z_2}) = (5 \times 10^{-4}, 5 \times 10^{-6})$ . The process noise has coefficient  $g(X_{k-1}) = 10^{-2} \text{diag}(X_{k-1})$ . The measurement process is defined by  $H = [I_{\overline{V}^2} \otimes M_{S_2}]$  with spectra  $(M_{S_1}, M_{S_2})$  collected at 10 equally-spaced wavelengths  $r \in [0, 50)$  through response functions  $m_{S_1}(r) = \exp\left(-\frac{(r-10)^2}{30}\right)$  and  $m_{S_2}(r) = \exp\left(-\frac{(r-40)^2}{30}\right)$ .