

Filtering SPDEs with Spatio-Temporal Point Process Observations

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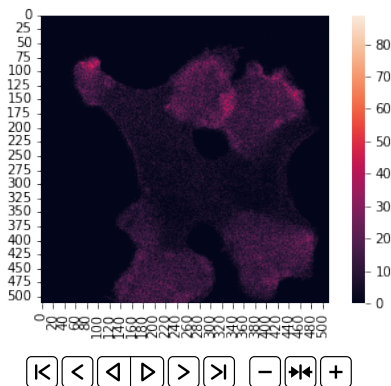
joint work with: J. Szalankiewicz, C. Martinez-Torres
[arXiv:2408.15920](https://arxiv.org/abs/2408.15920)

IMSI - U of Chicago, October 6, 2025



Motivation I. Statistics on intracellular wave dynamics

Example actin dynamics in *D. Discoideum* cells

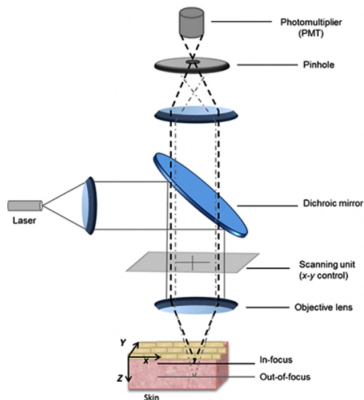


What do we really see?

Not actin concentration $X(t)$ but photon count $Y(t)$ (correlated with $X(t)$)!

Motivation II. From Actin Waves to Photon Counts

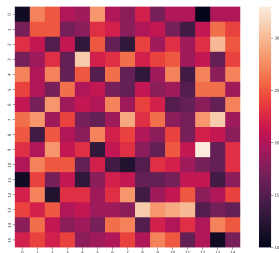
Confocal laser scanning microscopy (CLSM)



- ▶ CLSM (Confocal Laser Scanning Microscopy) records **photon counts**, not direct actin concentration
- ▶ Fluorescent biomarkers attached to actin emit photons when excited by laser
- ▶ Photon count $Y(t)$ follows **Poisson distribution**
- ▶ Poisson intensity parameter $\lambda = f(X(t))$ where $X(t)$ is the true underlying actin concentration
- ▶ **Challenge** Reconstruct $X(t)$ from noisy measurements $Y(t)$

Data analysis I

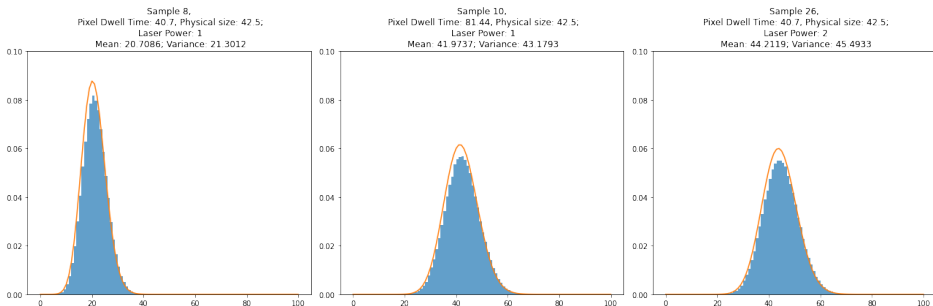
- ▶ analyzed images of Fluorescein solutions at varying concentrations and microscope configurations to validate the assumption of Poisson-distributed observation noise ("shot noise")¹
- ▶ assumed constant Fluorescein concentration during observations due to minimal diffusion over short time periods and localized regions
- ▶ Example image:



¹Krull et al., Image Denoising and the Generative Accumulation of Photons, preprint, arXiv:2307.06607, 2023

Data analysis II

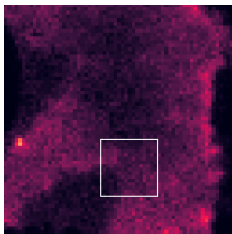
- ▶ data consists of sets of 10.000 images, every pixel treated as a sample of the same Fluorescin concentration
- ▶ Blue: Bar plot over all pixels of one data set
Orange: Poisson pdf with intensity given by empirical mean



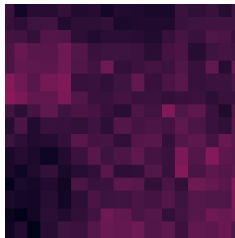
main feature variance scales linearly

Mathematical modelling

focus on an area of interest (AOI) to eliminate cell boundary effects



CLSM cell image



AOI

mathematical model: stoch. reaction-diffusion system

$$\partial_t u(t, x) = \vartheta \Delta u(t, x) + f(u, v)(t, x) + \dot{\xi}(t, x)$$

$$\partial_t v(t, x) = g(u, v)(t, x)$$

Agenda estimate $X(t) = [u(t, \cdot), v(t, \cdot)]$ from fluorescence microscopy data

$$Y(t, x) \sim \text{Pois} \left(\int_0^t \lambda(u(s, x)) ds \right)$$

from u (only), to infer on ϑ , f , g and μ

G. Pasemann, et al., Diffusivity Estimation for Activator - Inhibitor Models, J Nonlinear Sci '21

Part I:

Filtering SPDE with
marked point process (MPP) observations

Mathematical framework

signal process SPDE in the variational setting

$$\begin{cases} dX(t, x) = A(X(t, x)) dt + B(X(t, x)) dW(t, x), \\ X(0, x) = \xi(x), \end{cases} \quad (S)$$

on $\mathcal{H} := L^2(D)$, $D \subset \mathbb{R}^d$, w.r.t. a Gelfand triple $\mathcal{V} \hookrightarrow \mathcal{H} \equiv \mathcal{H}' \hookrightarrow \mathcal{V}'$ for some reflexive Banach space $\mathcal{V}$

standard ass. on A , B and W (Q - Wiener process with finite trace) (see [Liu, Röckner 2015])
imply unique variational solution $X \in L^2([0, T] \times \Omega, dt \otimes \mathbb{P}; \mathcal{H}) \cap L^2([0, T] \times \Omega, dt \otimes \mathbb{P}; \mathcal{V})$

observation process MPP Y on $[0, T] \times \mathcal{K}$, $\mathcal{K} \subset \mathbb{R}^{d_0}$ compact, directed by X with strictly positive and bounded conditional intensity $\lambda : [0, T] \times \mathcal{K} \times \mathcal{H} \rightarrow \mathbb{R}_+$ satisfying

$$0 < \underline{C} \leq \int_{\mathcal{K}} \lambda(t, x | X) \mu_{\mathcal{K}}(dx) \leq \overline{C} < \infty$$

where $\mu_{\mathcal{K}}$ denotes Lebesgue measure

On the observation process

Some properties of Y

- for measurable $\Gamma \subset \mathcal{K}$, $Y_\Gamma(t) := Y((0, t] \times \Gamma)$ admits the semi-martingale decomposition

$$\begin{cases} dY_\Gamma(t) = \lambda_\Gamma(t \mid X(t)) dt + dN_\Gamma(t), & t \in (0, T], \\ Y_\Gamma(0) = 0, \end{cases} \quad (0)$$

with

- ▶ $\lambda_\Gamma(t \mid X(t)) = \int_\Gamma \lambda(t, x \mid X(t)) \mu_\mathcal{K}(dx)$
- ▶ $N_\Gamma(t) = Y_\Gamma(t) - \int_0^t \lambda_\Gamma(s \mid X(s)) ds$

- the special case $Y^\mathcal{G}(t) := Y_\mathcal{K}(t)$ leads to the ground process with ass cond. intensity

$$\lambda^\mathcal{G}(t \mid X(t)) = \int_\mathcal{K} \lambda(t, x \mid X(t)) \mu_\mathcal{K}(dx)$$

Kallianpur-Striebel formula

Consider the $\mathbb{P}$ -martingale

$$\hat{Z}(t) := \exp \left\{ - \int_0^t \int_{\mathcal{K}} \log \{ \lambda(s-, x \mid X(s)) \} Y(ds, dx) \right. \\ \left. + \int_0^t \int_{\mathcal{K}} (\lambda(s, x \mid X(s)) - 1) \mu_{\mathcal{K}}(dx) ds \right\}, \quad t \in [0, T],$$

then $X_{0:t}$ and $Y_{0:t}$ are independent under $\mathbb{Q}$, where $\frac{d\mathbb{Q}}{d\mathbb{P}}|_{\mathcal{F}_t} = \hat{Z}_t$

since $Y_{0:T}$ under $\mathbb{Q}$ is a homogeneous Poisson point process

implies that for $Z(t) := \hat{Z}_t^{-1} = \frac{d\mathbb{P}}{d\mathbb{Q}}|_{\mathcal{F}_t}$

$$\frac{\mathbb{E}_{\mathbb{Q}}[\psi(X(t))Z(t)|\mathcal{Y}_t]}{\mathbb{E}_{\mathbb{Q}}[Z(t)|\mathcal{Y}_t]}$$

defines a regular conditional expectation of $\psi(X(t))$ given $Y_{0:t}$, $t \in [0, T]$

Filtering equations

Theorem

- **Zakai equation** For ψ sufficiently smooth, $\rho_t(\psi) := \mathbb{E}_{\mathbb{Q}}[\psi(X(t))Z(t)|\mathcal{Y}_t]$ solves

$$\begin{aligned} \rho_t(\psi) = & \rho_0(\psi) + \int_0^t \rho_s(\mathcal{L}\psi) ds \\ & + \int_0^t \int_{\mathcal{K}} \rho_{s-}((\lambda(s-, x | \cdot) - 1)\psi)(Y(ds, dx) - \mu_{\mathcal{K}}(dx) ds), \quad \mathbb{Q}\text{-a.s.} \end{aligned}$$

where

$$\mathcal{L}\psi = \nu' \langle A(\cdot), D^1\psi \rangle_{\mathcal{V}} + \frac{1}{2} \text{trace}\{B(\cdot)QB(\cdot)^* D^2\psi\}$$

- **Kushner-Stratonovich equation** For ψ sufficiently smooth, $\eta_t(\psi) := \frac{\mathbb{E}_{\mathbb{Q}}[\psi(X(t))Z(t)|\mathcal{Y}_t]}{\mathbb{E}_{\mathbb{Q}}[Z(t)|\mathcal{Y}_t]}$ solves

$$\begin{aligned} \eta_t(\psi) = & \eta_0(\psi) + \int_0^t \eta_s(\mathcal{L}\psi) ds \\ & + \int_0^t \int_{\mathcal{K}} \frac{\eta_{s-}(\psi \lambda(s-, x | \cdot)) - \eta_{s-}(\psi)\eta_{s-}(\lambda(s-, x | \cdot))}{\eta_{s-}(\lambda(s-, x | \cdot))} \times \\ & \times (Y(ds \times dx) - \eta_{s-}(\lambda(s-, x | \cdot)) \mu_{\mathcal{K}}(dx) ds) \end{aligned}$$

Finite dimensional observations

Let $\{K_1, \dots, K_M\}$ be a meas. partition of $\mathcal{K}$, then

$$Y^M(t) := (Y_{K_1}(t), \dots, Y_{K_M}(t))$$

defines a multivariate M -dim point process with conditional intensities

$$\lambda_i^M(t \mid X(t)) = \lambda_{K_i}(t \mid X(t)) = \int_{K_i} \lambda(t, x \mid X(t)) \mu_{\mathcal{K}}(dx)$$

Kallianpur-Striebel formula Let

$$Z^M(t) := \exp \left\{ \sum_{i=1}^M \left[\int_0^t \log \left\{ \frac{\lambda_i^M(s \mid X(s))}{\mu_{\mathcal{K}}(K_i^M)} \right\} dY_i^M(s) - \int_0^t (\lambda_i^M(s \mid X(s)) - \mu_{\mathcal{K}}(K_i^M)) ds \right] \right\}$$

then

$$\frac{\mathbb{E}_{\mathbb{Q}}[\psi(X(t))Z^M(t) \mid \mathcal{Y}_t]}{\mathbb{E}_{\mathbb{Q}}[Z^M(t) \mid \mathcal{Y}_t]}$$

defines a regular conditional expectation of $\psi(X(t))$ given $Y_{0:t}^M$.

Filtering equations for finite dimensional observations

Theorem

- **Zakai equation** $\rho_t^M(\psi) := \mathbb{E}_{\mathbb{Q}}[\psi(X(t))Z^M(t)|Y_{0:t}^M]$ solves

$$\begin{aligned}\rho_t^M(\psi) &= \rho_0^M(\psi) + \int_0^t \rho_s^M(\mathcal{L}\psi) ds \\ &+ \sum_{i=1}^M \int_0^t \rho_{s-}^M((\lambda_i^M(s-|\cdot) - 1)\psi)(Y_i^M(ds) - \mu_{K_i}(K_i) ds), \quad \mathbb{Q}\text{-a.s.}\end{aligned}$$

- **Kushner-Stratonovich equation** $\eta_t^M(\psi) := \frac{\mathbb{E}_{\mathbb{Q}}[\psi(X(t))Z^M(t)|Y_{0:t}^M]}{\mathbb{E}_{\mathbb{Q}}[Z^M(t)|Y_{0:t}^M]}$ solves

$$\begin{aligned}\eta_t^M(\psi) &= \eta_0^M(\psi) + \int_0^t \eta_s^M(\mathcal{L}\psi) ds \\ &+ \sum_{i=1}^M \int_0^t \frac{\eta_{s-}^M(\psi \lambda_i^M(s-|\cdot)) - \eta_{s-}^M(\psi) \eta_{s-}^M(\lambda_i^M(s-|\cdot))}{\eta_{s-}^M(\lambda_i^M(s-|\cdot))} \times \\ &\quad \times (Y_i^M(ds) - \eta_{s-}^M(\lambda_i^M(s-|\cdot)) ds)\end{aligned}$$

Convergence of finite dim observations

Prop Let

- ▶ $\mathcal{K}^M = \{K_1^M, \dots, K_{n_M}^M\}$ be an increasing set of meas. partitions of $\mathcal{K}$ separating pts of $\mathcal{K}$,
- ▶ $k_i^M \in K_i^M$ be representative pts of the set K_i^M ,
- ▶ $\tilde{Y}^M := \sum_{i=1}^M \sum_{\tau_i \in Y_i^M([0, T])} \delta_{\tau_i \times k_i^M}$.

Then

$$\|\tilde{Y}^M - Y\|_{BL}^* \leq Y([0, T] \times \mathcal{K}) \cdot \max_{1 \leq i \leq n_M} \text{diam}(K_i^M)$$

where

$$\|\mu\|_{BL}^* := \sup_{\substack{f: [0, T] \times \mathcal{K} \rightarrow \mathbb{R} \\ \|f\|_{\text{Lip}} + \|f\|_{\infty} \leq 1}} \int_{[0, T] \times \mathcal{K}} f \, d\mu$$

In particular, $\max_{1 \leq i \leq n_M} \text{diam}(K_i^M) \rightarrow 0$ implies $\tilde{Y}^M \rightarrow Y$ weakly.

Asymptotic consistency of posterior distribution I

Theorem Assume now $\lambda(t, x \mid X)$ continuous in (t, x, X) with

$$0 < \lambda_- := \inf_{(t,x,X)} \lambda(t, x \mid X) \leq \sup_{(t,x,X)} \lambda(t, x \mid X) =: \lambda_+ < \infty.$$

Let ρ_t^M be the unnormalized conditional distribution of $X(t)$ given $\tilde{Y}_{0:t}^M$. Then

- (i) $\|\rho_t^M - \rho_t\|_{\text{TV}} \longrightarrow 0$ $\mathbb{P}$ -a.s.
- (ii) If $\|\lambda(\cdot, \cdot \mid u)\|_{\text{Lip}} \leq L_\lambda$ for all $u \in \mathcal{H}$ and some deterministic Lipschitz constant L_λ , then

$$\sup_{t \in (0, T]} \|\rho_t^M - \rho_t\|_{\text{TV}} \leq \kappa_\rho(\lambda, Y) \max \left\{ \overline{\text{diam}}(\mathcal{K}^M), \overline{\text{diam}}(\mathcal{K}^M)^{Y^{\mathcal{G}}((0, T])} \right\}$$

with

$$\begin{aligned} \kappa_\rho(\lambda, Y) := & \frac{1}{2} \left((1 + L_\lambda \lambda_-^{-1})^{Y^{\mathcal{G}}((0, T])} - 1 \right) \cdot \\ & \max \left\{ \lambda_+^{Y^{\mathcal{G}}((0, T])} \exp\{-T(\lambda_- - 1)\mu_{\mathcal{K}}(\mathcal{K})\}, \right. \\ & \left. \lambda_+^{Y^{\mathcal{G}}((0, T])}, \exp\{-T(\lambda_- - 1)\mu_{\mathcal{K}}(\mathcal{K})\} \right\}. \end{aligned}$$

Asymptotic consistency of posterior distribution II

Corollary Let the assumptions of the previous Theorem hold true. Let η_t^M be the normalized conditional distribution of $X(t)$ given $\tilde{Y}_{0:t}^M$. Then

- (i) $\|\eta_t^M - \eta_t\|_{TV} \longrightarrow 0$ $\mathbb{P}$ -a.s.
- (ii) If $\lambda(t, x \mid u)$ is Lipschitz continuous w.r.t. (t, x) with Lipschitz constant L_λ uniform in u and ω then

$$\sup_{t \in [0, T]} \|\eta_t^M - \eta_t\|_{TV} \leq \kappa_\eta(\lambda, Y) \max \left\{ \overline{\text{diam}}(\mathcal{K}^M), \overline{\text{diam}}(\mathcal{K}^M)^{Y^{\mathcal{G}}((0, T])} \right\}$$

with

$$\begin{aligned} \kappa_\eta(\lambda, Y) := & \left((1 + L_\lambda \lambda_-^{-1})^{Y^{\mathcal{G}}((0, T])} - 1 \right) \cdot \\ & \max \left\{ \lambda_-^{-Y^{\mathcal{G}}((0, T])} \exp\{-2T(\lambda_- - 1)\mu_{\mathcal{K}}(\mathcal{K})\}, \right. \\ & \left(\frac{\lambda_+^2}{\lambda_-} \right)^{Y^{\mathcal{G}}((0, T])} \exp\{T(\lambda_+ + 1 - 2\lambda_-)\mu_{\mathcal{K}}(\mathcal{K})\}, \\ & \left. \lambda_+^{2Y^{\mathcal{G}}((0, T])} \exp\{T(\lambda_+ - 1)\mu_{\mathcal{K}}(\mathcal{K})\} \right\} \end{aligned}$$

Partial observations I

assume only partial observations from K_i^M , $i \in \mathcal{I}_M \subset \{1, \dots, n_M\}$

likelihood in this case reduces to

$$Z_{\mathcal{I}_M}^M(t) := \exp \left\{ \sum_{i \in \mathcal{I}_M} \int_0^t \log \left\{ \frac{\lambda_i^M(s | X(s))}{\mu_{\mathcal{K}}(K_i^M)} \right\} dY_i^M(s) - \int_0^t (\lambda_i^M(s | X(s)) - \mu_{\mathcal{K}}(K_i^M)) ds \right\}$$

using

$$\|\rho_t - \rho_t^{\mathcal{I}_M}\|_{\text{TV}} \leq \|\rho_t - \rho_t^M\|_{\text{TV}} + \|\rho_t^M - \rho_t^{\mathcal{I}_M}\|_{\text{TV}}$$

and controlling the second term yields error bounds

Partial observations: error bounds I

Proposition Let the assumptions from the previous Theorem hold true. Then

(i)

$$\|\rho_t - \rho_t^{\mathcal{I}_M^C}\|_{\text{TV}} \leq \kappa_\rho(\lambda, Y) \max \left\{ \overline{\text{diam}}(\mathcal{K}^M), \overline{\text{diam}}(\mathcal{K}^M)^{Y^{\mathcal{G}}((0, T])} \right\} \\ + \varepsilon_\rho(\lambda, Y)(\mathcal{K}(\mathcal{I}_M^C)),$$

with $\kappa_\rho(\lambda, Y)$ being the constant from the previous Theorem and

$$\varepsilon_\rho(\lambda, Y)(\mathcal{K}(\mathcal{I}_M^C)) := \\ \frac{1}{2} \max \left\{ \lambda_+^{Y^{\mathcal{G}}((0, T])} \exp\{-T(\lambda_- - 1)\mu_{\mathcal{K}}(\mathcal{K})\}, \right. \\ \left. \lambda_+^{Y^{\mathcal{G}}((0, T])}, \exp\{-T(\lambda_- - 1)\mu_{\mathcal{K}}(\mathcal{K})\} \cdot \right. \\ \left. \cdot \left(\exp \left\{ \max \{ |\log\{\lambda_- \}|, |\log\{\lambda_+ \}| \} Y((0, T] \times \mathcal{K}^M(\mathcal{I}_M^C)) \right\} + \right. \right. \\ \left. \left. + T\mu_{\mathcal{K}}(\mathcal{K}^M(\mathcal{I}_M^C)) \max\{|\lambda_- - 1|, |\lambda_+ - 1|\} \right\} - 1 \right) \right\}.$$

Partial observations: error bounds II

Proposition Let the assumptions from the previous Theorem hold true. Then

(i)

$$\|\rho_t - \rho_t^{\mathcal{I}_M}\|_{\text{TV}} \leq \kappa_\rho(\lambda, Y) \max \left\{ \overline{\text{diam}}(\mathcal{K}^M), \overline{\text{diam}}(\mathcal{K}^M)^{Y^{\mathcal{G}}((0, T])} \right\} \\ + \varepsilon_\rho(\lambda, Y)(\mathcal{K}(\mathcal{I}_M^C)),$$

(ii)

$$\|\eta_t - \eta_t^{\mathcal{I}_M}\|_{\text{TV}} \leq \kappa_\eta(\lambda, Y) \max \left\{ \overline{\text{diam}}(\mathcal{K}^M), \overline{\text{diam}}(\mathcal{K}^M)^{Y^{\mathcal{G}}((0, T])} \right\} \\ + \varepsilon_\eta(\lambda, Y)(\mathcal{K}(\mathcal{I}_M^C)),$$

with $\kappa_\eta(\lambda, Y)$ being the constant from the previous Corollary and

$$\varepsilon_\eta(\lambda, Y)(\mathcal{K}(\mathcal{I}_M^C)) \\ := \max \left\{ \lambda_-^{-Y((0, t] \times \mathcal{K}^M(\mathcal{I}_M))} \exp\{-2t(\lambda_- - 1)\mu_{\mathcal{K}}(\mathcal{K})\}, \right. \\ \lambda_+^{2Y^{\mathcal{G}}((0, t])} \lambda_-^{-Y((0, t] \times \mathcal{K}^M(\mathcal{I}_M))} \\ \cdot \exp\{t((\lambda_+ + 1)\mu_{\mathcal{K}}(\mathcal{K}^M(\mathcal{I}_M)) - 2\lambda_- \mu_{\mathcal{K}}(\mathcal{K}))\}, \\ \lambda_+^{2Y^{\mathcal{G}}((0, t])} \exp\{t(\lambda_+ - 1)\mu_{\mathcal{K}}(\mathcal{K}^M(\mathcal{I}_M))\} \} \\ \cdot \left(\exp \left\{ \max \{ |\log \{\lambda_- \}|, |\log \{\lambda_+ \}| \} Y((0, t] \times \mathcal{K}^M(\mathcal{I}_M^C)) \right. \right. \\ \left. \left. + t\mu_{\mathcal{K}}(\mathcal{K}^M(\mathcal{I}_M^C)) \max\{|\lambda_- - 1|, |\lambda_+ - 1|\} \right\} - 1 \right).$$

Part II:

Numerical Experiments and Application

Synthetic data I

- Signal: Activator process u from SPDE system

$$\begin{cases} du(t) = (\Delta u(t) + \varepsilon(u(t) - \alpha_1)(u(t) - \alpha_2)(\alpha_3 - u(t)) - v(t) + I)dt + B dW_1(t), \\ dv(t) = (\Delta v(t) + \gamma(\beta u(t) - v(t)))dt + \vartheta dW_2(t), \end{cases} \quad (1)$$

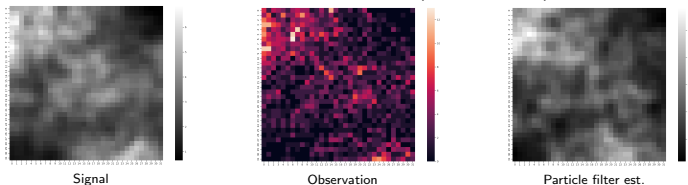
- Observations: Marked Cox processes with spatial resolutions $32 \times 32, \dots, 1 \times 1$. Intensity of the form:

$$\lambda(t, x) := e^{-at}(cx)^2 \vee C_{\max} \quad (2)$$

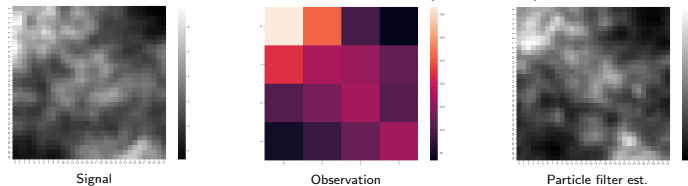
- Particle filter with 20 particles. Initialization with correct parameters and "close enough" initial condition.

Synthetic data II

Comparison for a fixed time step (32×32 pixels)

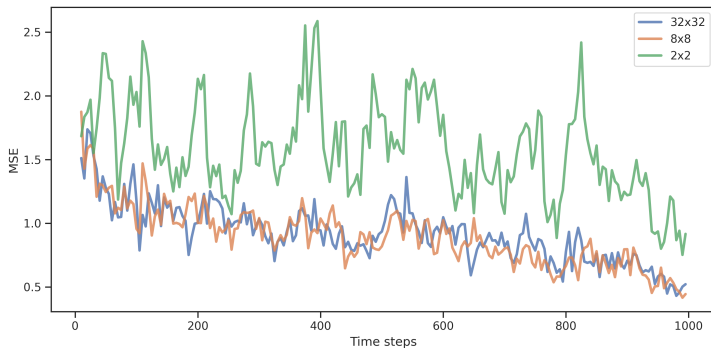


Comparison for a fixed time step (4×4 pixels)



Synthetic data III

- ▶ $M :=$ spatial resolution, $L :=$ ensemble size
- ▶ $\bar{X}_L^M(t_j) := \frac{1}{L} \sum_{i=1}^L X_{L,i}^M(t_j) \approx X(t_j)$
- ▶ $\text{MSE}(\bar{X}_L^M, X)(t_j) := \sqrt{\frac{1}{|\text{pixels}|} \sum_{\text{pixels}} (\bar{X}_L^M(t_j, \text{pixel}) - X(t_j, \text{pixel}))^2}$



Empirical spatial MSE between particle filter estimates and signal

Wrong noise assumption I

- ▶ Assume: observation noise is Gaussian

- ▶ Estimate the empirical variances $\hat{\sigma}^2$ of Y

- ▶ Poisson distributed observation leads to

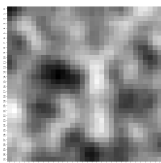
$$\hat{\sigma}^2 dt \approx \lambda^k(t, X(t)) dt, \quad k = \text{pixel}.$$

"Wrong" observation dynamics

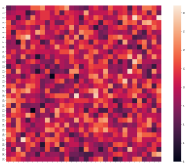
$$d\tilde{Y}^k(t) = \lambda^k(t, X(t)) dt + \hat{\sigma} dB^k(t)$$

with B being a k -dim. Brownian motion on $[0, T]$.

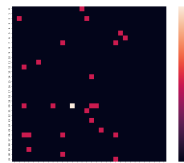
- ▶ Test for high and low intensity observations:



Signal $X(t)$

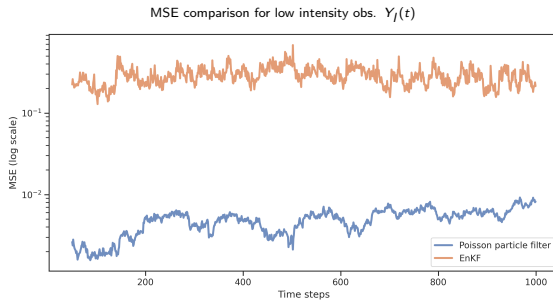
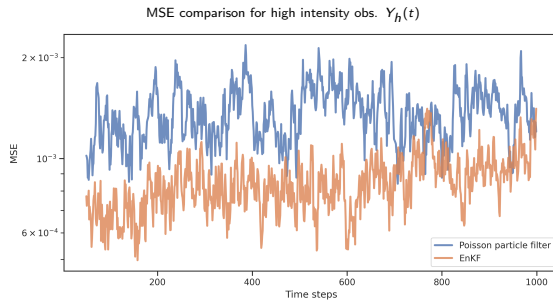


High intensity observation $Y_h(t)$



Low intensity observation $Y_l(t)$

Wrong noise assumption II

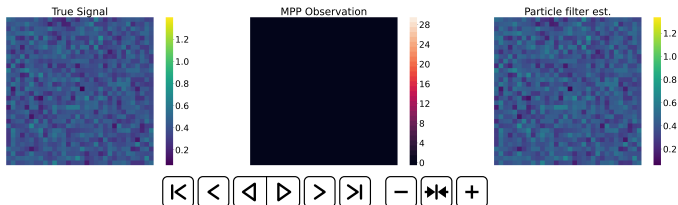


Application to CLSM recordings I

- ▶ used reaction-diffusion SPDE with FitzHugh-Nagumo nonlinearity as model for the signal, parameters calibrated to keep activator values between 0 and 1, matching observed actin concentration data
- ▶ adjusted observation intensity to align simulated photon counts with the data

Particle filter: (100k particles, 32x32, 1000 steps)

Particle filter run (Ensemble size: 1000) with SPDE signal and MPP observation
 $t = 0$



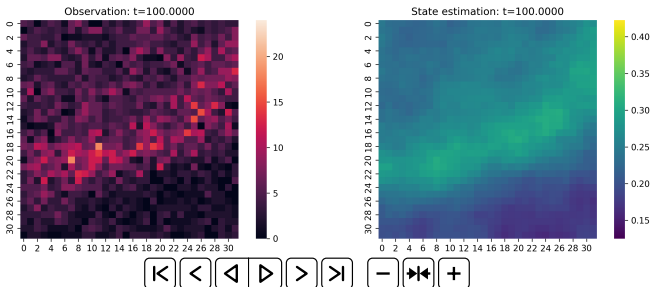
Application to CLSM recordings II

Ongoing work: state-parameter estimation

to test hypotheses on difference in wave mobility (e.g. spatial diffusivity) in dependence of different substrates

State-Parameter Particle filter: (500k particles, 32x32, 1000 steps, run on HPC cluster)

Comparison of sample n300_G6_roi_22 and state estimation over time
 $t = 100$



References

- ▶ J. Szalankiewicz, C. Martinez-Torres, W. Stannat: Filtering SPDEs with Spatio-Temporal Point Process Observations, arXiv:2408.15920
- ▶ G. Pasemann, C. Beta, W. Stannat: Stochastic Reaction-Diffusion Systems in Biophysics: Towards a Toolbox for Quantitative Model Evaluation, arXiv:2307.06655
- ▶ G. Pasemann, S. Flemming, S. Alonso, C. Beta, W. Stannat: Diffusivity estimation for activator-inhibitor models: Theory and application to intracellular dynamics of the actin cytoskeleton, J. Nonlinear Sci. 31, 2021
- ▶ G. Pasemann, W. Stannat: Drift estimation for stochastic reaction-diffusion systems, Electron. J. Statist. 14, 2020

Thank you for your attention!