# Visualizing nucleosome cluster dynamics with dense single molecule localization microscopy

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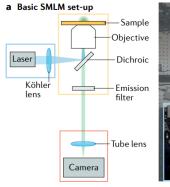
Introduction

Visualizing nucleosome cluster dynamics

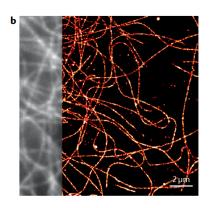
# Methods

Direct stochastic optical reconstruction microscopy

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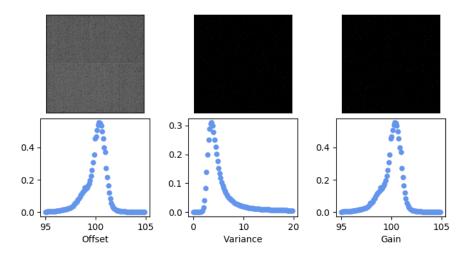




Direct stochastic optical reconstruction microscopy

#### Readout noise of sCMOS cameras

Hamamatsu ORCA v3 CMOS, air cooled to -10C



Measured signal:  $H_k = S_k + \xi_k$ ,  $S_k \sim \text{Poisson}(\mu_k), \xi_k \sim \mathcal{N}(o_k, \sigma_k^2)$ 

#### Maximum likelihood localization of an isolated fluorescent emitter

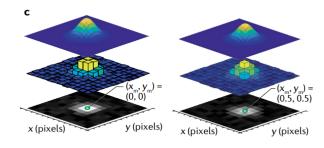
Localization: 
$$\theta^* = \operatorname*{argmax}_{\theta} \prod_k P(H_k | \theta) = \operatorname*{argmin}_{\theta} - \sum_k \log P(H_k | \theta)$$

$$\mu_k = g_k \frac{\eta}{N_0} \Delta \int_{\text{pixel}} G(x, y) dA$$

 $\eta$  – quantum efficiency

 $N_0$  – emission rate

 $\Delta$  – exposure time

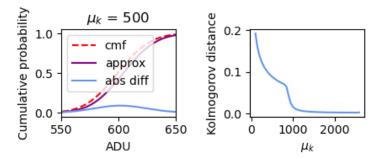


$$P(H_k|\theta) = A \sum_{r=0}^{\infty} \frac{1}{q!} e^{-\mu_k} \mu_k^q \frac{1}{\sqrt{2\pi}\sigma_k} e^{-\frac{(H_k - g_k q - o_k)}{2\sigma_k^2}}$$

 $P(H_k|\theta)$  can be approximated as Poisson at high signal-to-noise (SNR)

## Quality of the Poisson approximation depends on SNR

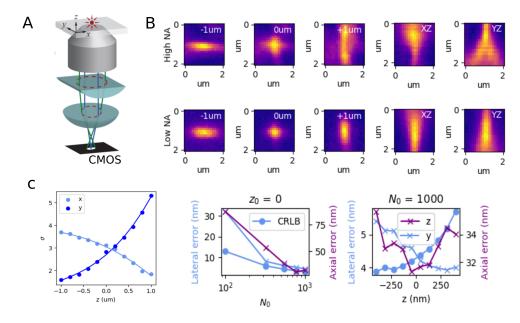
$$P(H_k|\theta) \approx \mathrm{Poisson}(\mu_k + \sigma_k^2)$$
 for  $N_0 > 500$  asssuming  $\Delta = 100$ ms



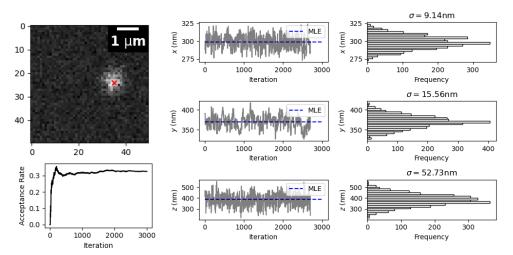
Using the approximation we can write

$$\ell(\vec{H}|\theta) = -\log \prod_{k} \frac{e^{-\left(\mu_{k}^{\prime}\right)} \left(\mu_{k}^{\prime}\right)^{n_{k}}}{n_{k}!} = \sum_{k} \log n_{k}! + \mu_{k}^{\prime} - n_{k} \log \left(\mu_{k}^{\prime}\right)$$

### Estimator precision sets the resolution limit in localization microscopy

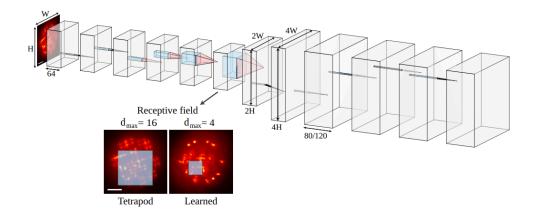


# Estimator precision sets the resolution limit in localization microscopy



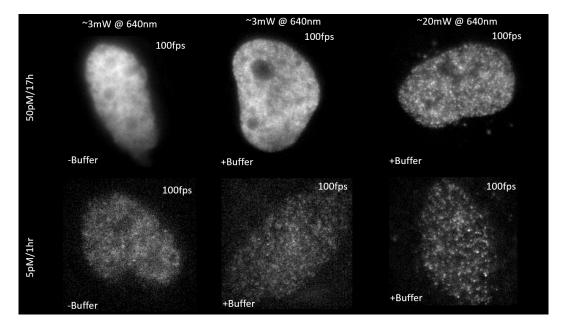
- ▶ Localization uncertainty can be quantified with Metropolis-Hastings MCMC
- ► MCMC is asymptotically exact, but slow

# Deep learning beats MLE at 2D and 3D localization

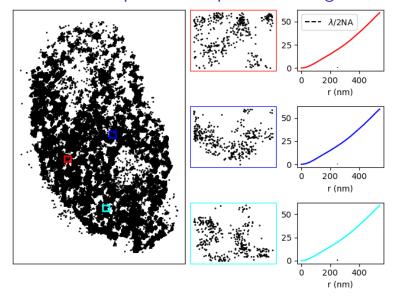


Deep learning beats MLE at 2D and 3D localization

# The metastable OFF state can be maintained with high laser power



## Resolution is dependent on photoswitching kinetics



#### Resolution is dependent on photoswitching kinetics

A molecule is considered "detected" in principle if the measured ADU signal satisfies  $\tilde{s} = \mu \tau \geq \delta$  where  $\delta$  is a number of photons which satisfy a criterion on localization accuracy.

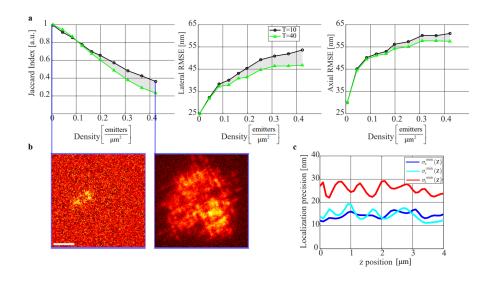
$$\alpha = \int_{\delta}^{\Delta} \left( \sum_{n=0}^{\infty} Q(N=n) \psi(\tau|n; \vec{k}) \right) d\tau \approx \underset{\tau \sim P(\tau)}{\mathbb{E}} (\mathbb{I}[\tau > \delta])$$

 $P(\tau)$  is usually obtained by Monte Carlo simulation. This is useful for computing density measures and the total acquisition time:

$$D = lpha K \left( rac{\lambda}{2 \mathrm{NA}} 
ight) \ \ T = \left( \Delta_{SR} + rac{2N}{\log(1 - lpha)} 
ight)^2$$

For actually inferring  $k_1, k_2$ , we need a measure of distance between  $P(\tilde{s})$  and  $P(s|k_1, k_2)$  for many  $k_1, k_2$  pairs. Luckily we only need to compute  $P(s|k_1, k_2)$  once, and we can then perform a grid search

### Resolution is dependent on photoswitching kinetics



# Results

Diffusion of H2B-JF549 depends on local nucleosome organization