# Bayesian image reconstruction

Clayton W. Seitz

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# Outline

References

# Bayesian image reconstruction

Say a fluorophore emits photons at a rate $\lambda_n$. This is the best we can do according to QM

For a CMOS array with quantum efficiency $\gamma \; [e^-/p]$ we have

$$I_n = \gamma g_n P_n(\lambda_n) + G_n(\mu_n; \sigma_n^2) + \beta$$

where $\mu_n \; [\mathrm{ADU}]$ is the detector offset and $g_n \; [\mathrm{ADU}/e^-]$ is the gain.

All we know is $\lambda_n$, so both the true signal $I_n$ and the detected signal $\hat{I}_n$ are stochastic processes.

$$P_\lambda(I_n, \hat{I}_n) = \frac{1}{Z}\frac{\exp\left(-\lambda_n\right)\lambda_n^p}{p!}\exp\left(-\frac{(D - g_n p - \mu_n)^2}{\sigma_n^2}\right)$$

# Bayesian image reconstruction

Marginalizing over $p$ gives the noise model as a function of the rate $\lambda_n$

$$P_\lambda(I_n) = \frac{1}{Z}\sum_p \frac{\exp\left(-\lambda_n\right)\lambda_n^p}{p!}\exp\left(-\frac{(D - g_n p - \mu_n)^2}{\sigma_n^2}\right)$$

# References I