## Precise Nanometer Localization Analysis for Individual Fluorescent Probes

 based on a paper by R.E. Thompson, D.R. Larson and W.W. Webb
## Outline

1. Motivation
2. Algorithms
a. Spot recognition
b. Fitting algorithms
3. Error estimation
4. Monte Carlo sample generation
5. Summary \& Outlook

## 1. Motivation

- Minimal resolution of light microscopes

$$
r \approx \frac{\lambda}{2} \approx 250 \mathrm{~nm} \text { (diffraction limit) }
$$

- (Left to right) A mammalian cell, a bacterial cell, a mitochondrion, an influenza virus, a ribosome, the green fluorescent protein, and a small molecule (thymine).


Source:
Huang et al., Breaking the Diffraction Barrier: Super-Resolution Imaging of
Cells, Cell 143 (2010), p. 1047-1058

- Airy disk $r \approx 0.61 \frac{\lambda}{N A}$ ( $N A \leq 1.6$ )

- Approximation by a Gaussian $\sigma \approx 0.42 \frac{\lambda}{N A}$


Source: en.wikipedia.org/wiki/Airy_disk

- Stochastical optical reconstruction microscopy (STORM)
- Reconstruction of spot centers
- Assumption: punctate and well-separated objects


## Source:

T.J. Gould, S.T. Hess, Nanoscale Biological Fluorescence Imaging: Breaking the Diffraction Barrier, Methods in Cell Biology 89 (2008), p. 329-358

- Aggravated by noise
- Background noise
- Photon shot noise



## 2. Algorithms

- Given: matrix of photon counts for each pixel
- 2.a. Spot recognition
- Find pixel values above some threshold (e.g. "8 standard deviations away from the mean")
- Look for local maxima
- Cut out a surrounding regions according to the potential spot
- Mean remaining cells to obtain the background mean
- Subtract the background mean from the spots
- Fit the spot centers


## 2.b. Fitting algorithms

- Given: matrix of photon counts $S_{i j}{ }^{\circ}{ }^{\circ}$
- Notations
- $(i, j)$ location of pixel center in local coordinates
- Spot center $\left(x_{0}, y_{0}\right)$ - unknown
- Number of photons in spot $N$ - unknown
- Standard deviation $\sigma$ - known
- $p_{G}(i, j)=\frac{1}{2 \pi \sqrt{\sigma}} \exp \left(-\frac{\left(i-x_{0}\right)^{2}}{2 \sigma^{2}}-\frac{\left(j-y_{0}\right)^{2}}{2 \sigma^{2}}\right)$
- We want: approximation of the center of $S_{i j}$ by fitting with a pixelated Gaussian, i.e.

$$
G_{i j}=N p_{G}(i, j)
$$

- Least squares approach, i.e. we want to minimize $\chi^{2}=\sum_{i, j} \frac{\left(s_{i j}-G_{i j}\right)^{2}}{\psi_{i j}^{2}}$ (here $\left.\psi_{i j}^{2}=\sigma^{2}+b^{2}\right)$
- For every minimum of $\chi^{2}$ :

$$
\begin{gathered}
\frac{d}{d x_{0}} \sum\left(S_{i j}-G_{i j}\right)^{2}=0 \\
\Leftrightarrow \sum 2\left(S_{i j}-G_{i j}\right) \frac{\left(i-x_{0}\right)}{\sigma^{2}} G_{i j}=0 \\
\Leftrightarrow \sum S_{i j} G_{i j}\left(i-x_{0}\right)+\sum G_{i j}^{2}\left(i-x_{0}\right)=0
\end{gathered}
$$

- Full least squares

$$
x_{0}=\frac{\sum i\left(S_{i j}-G_{i j}\right) G_{i j}}{\sum\left(S_{i j}-G_{i j}\right) G_{i j}}
$$

- Odd symmetry: $\sum G_{i j}^{2}\left(i-x_{0}\right) \approx 0$
- Gaussian mask fitting

$$
x_{0}=\frac{\sum i S_{i j} G_{i j}}{\sum S_{i j} G_{i j}}=\frac{\sum i S_{i j} p_{G}(i, j)}{\sum S_{i j} p_{G}(i, j)}
$$

- Number of photons within spot

$$
N=\frac{\sum S_{i j} p_{G}(i, j)}{\sum p_{G}(i, j)^{2}}
$$

## 3. Error estimation

- Split into two cases
- Photon shot noise-limited (a)
- Background noise-limited (b)
- Case (a)
- No pixelation: $\left\langle(\Delta x)^{2}\right\rangle=\frac{\operatorname{Var}(x)}{N}=\frac{\sigma^{2}}{N}$
- Pixelation noise: $\left\langle(\Delta x)^{2}\right\rangle=\frac{\sigma^{2}+\frac{a^{2}}{12}}{N}$
pixel size $a, \frac{a^{2}}{12}$ is the variance of a top-hat distribution of size $a$

- Case (b)
- We minimized $\chi^{2}(x)=\sum \frac{\left(s_{i j}-G_{i j}(x)\right)^{2}}{\psi_{i j}^{2}}$
- 1-dimensional $\chi^{2}(x)=\sum \frac{\left(S_{k}-G_{k}(x)\right)^{2}}{\psi_{k}^{2}}$
- Background noise only $\psi_{k}=b(b \in R)$
- Taylor expansion

$$
G_{k}(x)=G_{k}\left(x_{0}\right)+\underbrace{\left(x-x_{0}\right)}_{\Delta x} G_{k}^{\prime}\left(x_{0}\right)+O\left((\Delta x)^{2}\right)
$$

- Denote $\Delta S_{k}=G_{k}\left(x_{0}\right)-S_{k}$

$$
\begin{gathered}
0=\frac{d}{d x} \chi^{2}=\sum 2 \frac{\left(\mathrm{~S}_{\mathrm{k}}-\mathrm{G}_{\mathrm{k}}(\mathrm{x})\right)}{b^{2}} G_{k}^{\prime}(x) \\
\stackrel{\leftrightarrow}{T E} 0=\sum\left(-\Delta S_{k}-\Delta x G_{k}^{\prime}\left(x_{0}\right)\right) G_{k}^{\prime}\left(x_{0}\right)+O\left((\Delta x)^{2}\right) \\
\Leftrightarrow 0=\sum \Delta S_{k} G_{k}^{\prime}\left(x_{0}\right)+\sum G_{k}^{\prime}\left(x_{0}\right)^{2} \Delta x+O\left((\Delta x)^{2}\right) \\
\Rightarrow \Delta x \approx-\frac{\sum \Delta S_{k} G_{k}^{\prime}\left(x_{0}\right)}{\sum G_{k}^{\prime}\left(x_{0}\right)^{2}}
\end{gathered}
$$

Now as $G_{k}^{\prime}\left(x_{0}\right)$ are constants

$$
\begin{gathered}
\left\langle\left(\Delta S_{k}\right)^{2}\right\rangle=\operatorname{Var}\left(S_{k}\right)=b^{2},\left\langle\Delta S_{k}\right\rangle=0 \\
\Rightarrow\left\langle\left(\Sigma \Delta S_{k} G_{k}^{\prime}\left(x_{0}\right)\right)^{2}\right\rangle=\left(\sum\left\langle\left(\Delta S_{k}\right)^{2}\right\rangle G_{k}^{\prime}\left(x_{0}\right)^{2}\right)=\sum b^{2} G_{k}^{\prime}\left(x_{0}\right)^{2} \\
\Rightarrow\left\langle(\Delta x)^{2}\right\rangle=\frac{b^{2}}{\sum G_{k}^{\prime}\left(x_{0}\right)^{2}}
\end{gathered}
$$

- From $G_{k}(x)=\frac{N}{\sqrt{2 \pi} \sigma} \exp \left(-\frac{(k-x)^{2}}{2 \sigma}\right)$ we derive

$$
\begin{aligned}
& G_{k}^{\prime}(x)=\frac{N}{\sqrt{2 \pi} \sigma^{2}}(k-x) \exp \left(-\frac{(k-x)^{2}}{2 \sigma}\right) \\
\Rightarrow & G_{k}^{\prime}(x)^{2}=\frac{N^{2}}{2 \pi \sigma^{4}}(k-x)^{2} \exp \left(-\frac{(k-x)^{2}}{\sigma}\right)
\end{aligned}
$$

Finally we use

- $\sum G_{k}^{\prime}\left(x_{0}\right)^{2} \approx a \int G_{k}^{\prime}\left(x_{0}\right)^{2} d k=$

$$
\frac{a N^{2}}{2 \pi \sigma^{4}} \int(k-x)^{2} \exp \left(-\frac{(k-x)^{2}}{\sigma^{2}}\right) d k=\frac{a N^{2}}{4 \sqrt{\pi} \sigma^{3}}
$$

to obtain

$$
\left\langle(\Delta x)^{2}\right\rangle=\frac{4 b^{2} \sqrt{\pi} \sigma^{3}}{a N^{2}}
$$

- Similarly in two dimensions

$$
\left\langle(\Delta x)^{2}\right\rangle=\frac{8 b^{2} \pi \sigma^{4}}{a^{2} N^{2}}
$$

- Altogether the sum of (a) and (b) yields

$$
\left\langle(\Delta x)^{2}\right\rangle \approx \frac{8 b^{2} \pi \sigma^{4}}{a^{2} N^{2}}+\frac{\sigma^{2}+\frac{a^{2}}{12}}{N}
$$

- Transition point

$$
N_{t}=\frac{8 b^{2} \pi \sigma^{4}}{a^{2}\left(\sigma^{2}+\frac{a^{2}}{12}\right)}
$$

- Analogously we obtain

$$
\left\langle(\Delta N)^{2}\right\rangle=N+\frac{4 \pi \sigma^{2} b^{2}}{a^{2}}
$$

## 4. Monte Carlo sample generation

- Basic algorithm
- Fix some (arbitrary) spot center
- Generate random photon positions (Gaussian distributed)
- Collect photons on coarse grid
- Add (Poisson distributed) background for every pixel
- Parameters
- Spot diameter, pixel size
- Number of photons in spot
- Background noise level
- Dependence on the photon number
- $N_{t} \approx 1317$ photons



$$
\left\langle(\Delta x)^{2}\right\rangle=\frac{8 b^{2} \pi \sigma^{4}}{a^{2} N^{2}}+\frac{\sigma^{2}+\frac{a^{2}}{12}}{N}
$$

Dependence on $\frac{\text { spot size }}{\text { pixel size }}=\frac{s}{a}$


- Underestimation due to
- First order Taylor approximation
- Interpolation between two limited cases
- Transformation of a discrete sum into an integral
- Assumption of $\frac{s}{a} \gg 1$
- Simplification of Least Squares
- Error in N



## 5. Summary \& Outlook

- Basic idea of achieving nanometer resolution in microscopy
- Construction of fitting Algorithms
- Simple, but rough estimates for the errors
- Application to experimental data, comparison with common software
- Check for potential improvements



## THANK YOU FOR YOUR ATTENTION!



Source: xkcd.com/435/

