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#### Hypothesis-based particle detection IDMxS for accurate nanoparticle counting DIGITAL MOLECULAR ANALYTICS & SCIENCE

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### Introduction

- Accurate quantification of individual biomolecules represents a fundamental shift from traditional diagnostics that rely on ensemble measurements of large molecular populations.
- Digital detection enables precise analysis of the concentration of low abundance analytes crucial for applications in early disease diagnostics and personalised healthcare [1,2].
- Nanoparticle imaging based assays are a powerful digital diagnostic tool where enumeration of surface bound particles provides direct, calibration-free quantification of analyte concentration [3].

#### **Performance analysis**

- Noisy simulated data used to assess performance characteris-tics of particle counting algorithm.
- Confusion tables were calculated and observed accuracies weighted by Poisson distribution to yield expected accuracy.
- Scattering strength: Accuracy improves for stronger scatterers due to increasing SNR and SBR.

	Baseline
σ	2 px

- Low signal levels e.g. from weak scattering, can lead to significant errors in particle detection, with generally unknown rates of false alarm.
- Probabilitistic methods, incorporating knowledge of noise sources can enable robust detection without arbitrary parameter tuning [4].
- We present a novel maximum likelihood hypothesis based approach for nanoparticle counting.

#### <u>Algorithm structure</u>

- Image segmentation with a rolling window divides large field of view into small regions containing only a few particles on average.
- Image modelled as a random Poisson process with mean intensity given by:

- intensity Background Reduced SBR degrades expected accuracy.
- **Point spread function**: broadening of PSF reduces intensity on each pixel and hence reduces SNR.
- Image zoom: competiting effects of reduced background and broader point spread function give optimal range.







$$\lambda(\mathbf{r}) = \lambda_{bg} + \sum_{k=1}^{N} \frac{I_k}{2\pi\sigma^2} \exp\left[-\frac{|\mathbf{r} - \mathbf{r}_k|^2}{2\sigma^2}\right]$$

- Model parameters for each image segment found via maximum likelihood estimation (MLE) for hypothesis that 0, 1, 2, ... particles are present.
- Preliminary coarse peak detection used to initalise MLE fitting.
- Out of bounds (oob) penalty applied to log-likelihood function to constrain allowed particle positions.

 $\mathcal{M} = \sum \left( v_i \log(\lambda_i) + \log(v_i!) \right) - \mathcal{P}_{\text{oob}}$ 





Each hypothesis scored using a modified log-likelihood function. The Laplace penalty term, using observed Fisher information matrix, reduces over fitting.

$$\mathcal{S} = \mathcal{M} - \frac{1}{-\log[\det \mathbb{I}]}$$



Probability of classifying two particles as a single particle:

 $p_{2\to 1} \approx 1 - \exp\left[-\pi R^2 s\right]$ 

Higher order classification errors approximately given by powers of  $p_{2 \rightarrow 1}$ .



Surface density  $R^2s$ 

#### $9^{108[000]}$

- Hypothesis with the highest score is selected yielding number of particles.
- Algorithm also provides particle properties for later analysis, e.g. classification.

### References

[1] A. S. Basu, SLAS Technology 22, 369–386 (2017). [2] D. C. Duffy, Lab Chip 23, 818–847 (2023). [3] E. Ferrari, Biosensors 13, 411 (2023). [4] C. S. Smith, S. Stallinga, et al., MBoC 26, 4057–4062 (2015).

## **Conclusions**

- We have presented a hypothesis-based particle detection algorithm for use in particle counting based nanoparticle imaging assays.
- Performance remains reliable for a diverse range of experimental conditions.
- Arbitrary parameter tuning or large training datasets are not required.







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