

Multivariate Curve Resolution for Hyperspectral Images

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Introduction

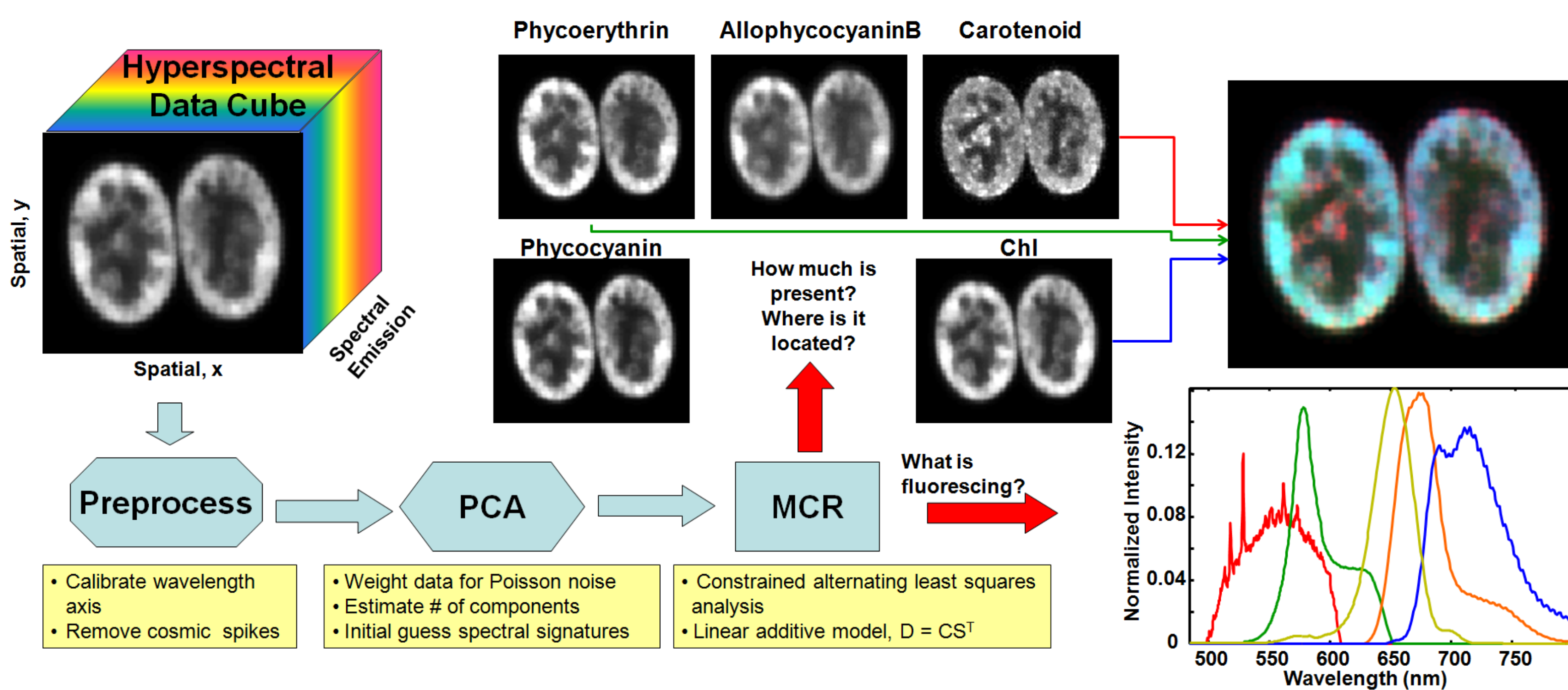
The application of Multivariate curve resolution (MCR) to hyperspectral images allows the determination of the number of different spectral components, their pure spectra, and their spatial distribution even for spectrally similar compounds. MCR is related to both principal component analysis (PCA) and independent component analysis (ICA), where all techniques resolve hyperspectral data into pure spectral components and concentrations while requiring little or no prior information. However, the three algorithms all find different solutions, each of which maximizes the explained variance of the data under the influence of a particular set of constraints. Whereas PCA and ICA which impose mathematically and statistically meaningful constraints, MCR applies physically and chemically meaningful constraints. Examples include requiring that concentrations cannot be negative and that fluorescence spectra cannot be negative.

Leveraging the physical and chemical constraints reduces the rotational ambiguity (non-uniqueness of the solution), facilitating the determination of the real spectra and concentrations. However, the alternating least squares optimization performed by MCR may sometimes become trapped in local rather than global minima, and a certain amount of rotational ambiguity generally remains. Additionally, MCR generally assumes that the noise is independent and ideally distributed (perfect Gaussian white noise),¹ whereas Poisson noise becomes highly significant for single-molecule biophysics experiments. I am currently extending Sandia's existing MCR algorithm to properly account for the noise, minimize the uncertainty, and quantify the remaining uncertainty.

Biophysical Applications of Hyperspectral Microscopy

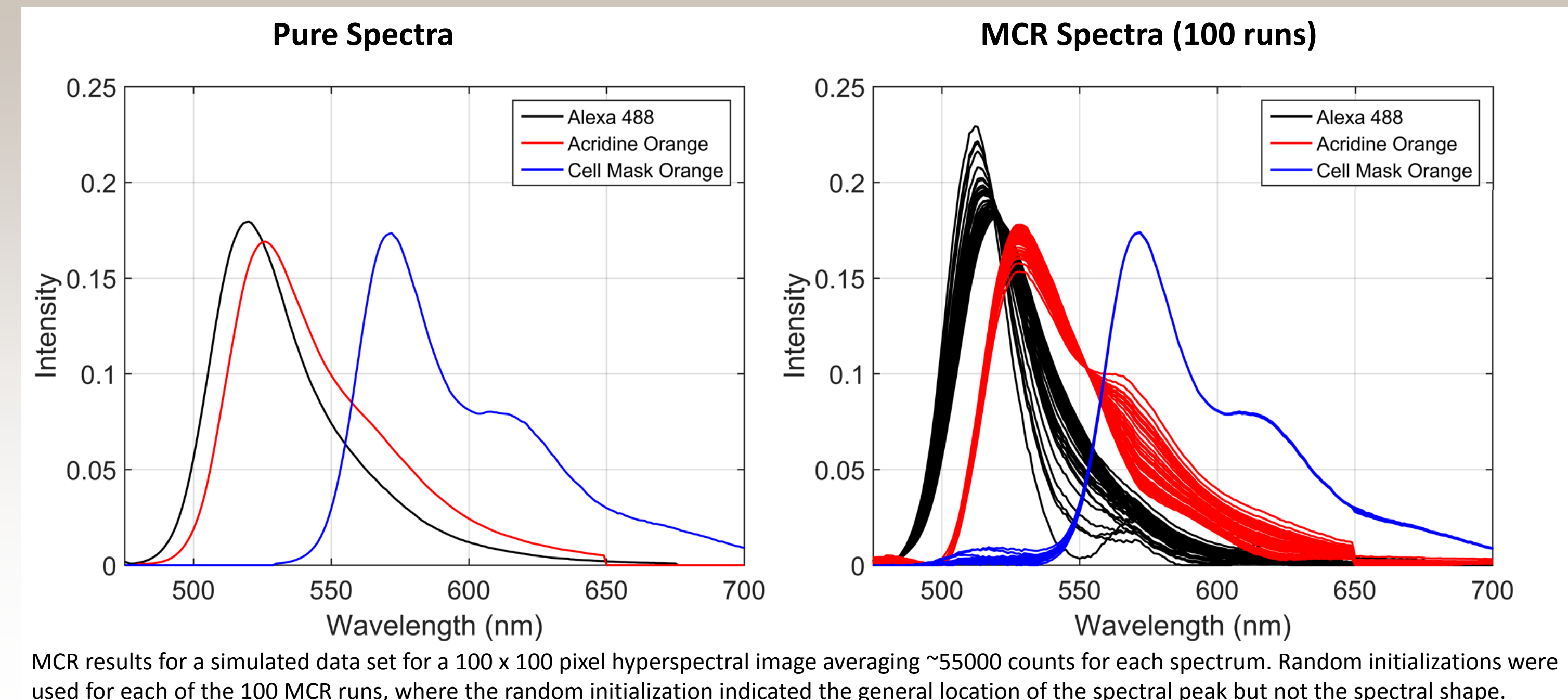
Hyperspectral microscopy greatly improves upon the spectral resolving power of traditional microscopy by measuring the entire emission spectrum for each voxel instead of at most a few distinct spectral bands for traditional, filter-based microscopes. The limited spectral resolution of traditional microscopes places severe constraints on the number of labels which can be used and the spectral similarity between labels, constraints which hyperspectral microscopy relaxes. Further, when only a few spectral bands are observed, auto-fluorescence can be nearly impossible to distinguish from the contributions of fluorescent probes measured at the single-molecule level. The combination of hyperspectral microscopy with MCR allows the contributions from the auto-fluorescence to be isolated. Currently, along with Jeri Timlin I am building a hyperspectral Stimulated Emission Depletion (hyperspectral STED) microscope.² Hyperspectral STED microscopy builds off the advances in spatial resolution made in recent years by various super-resolution microscopy techniques, providing analogous improvements in spectral resolution.

Example: Using MCR to Determine Chemical Species



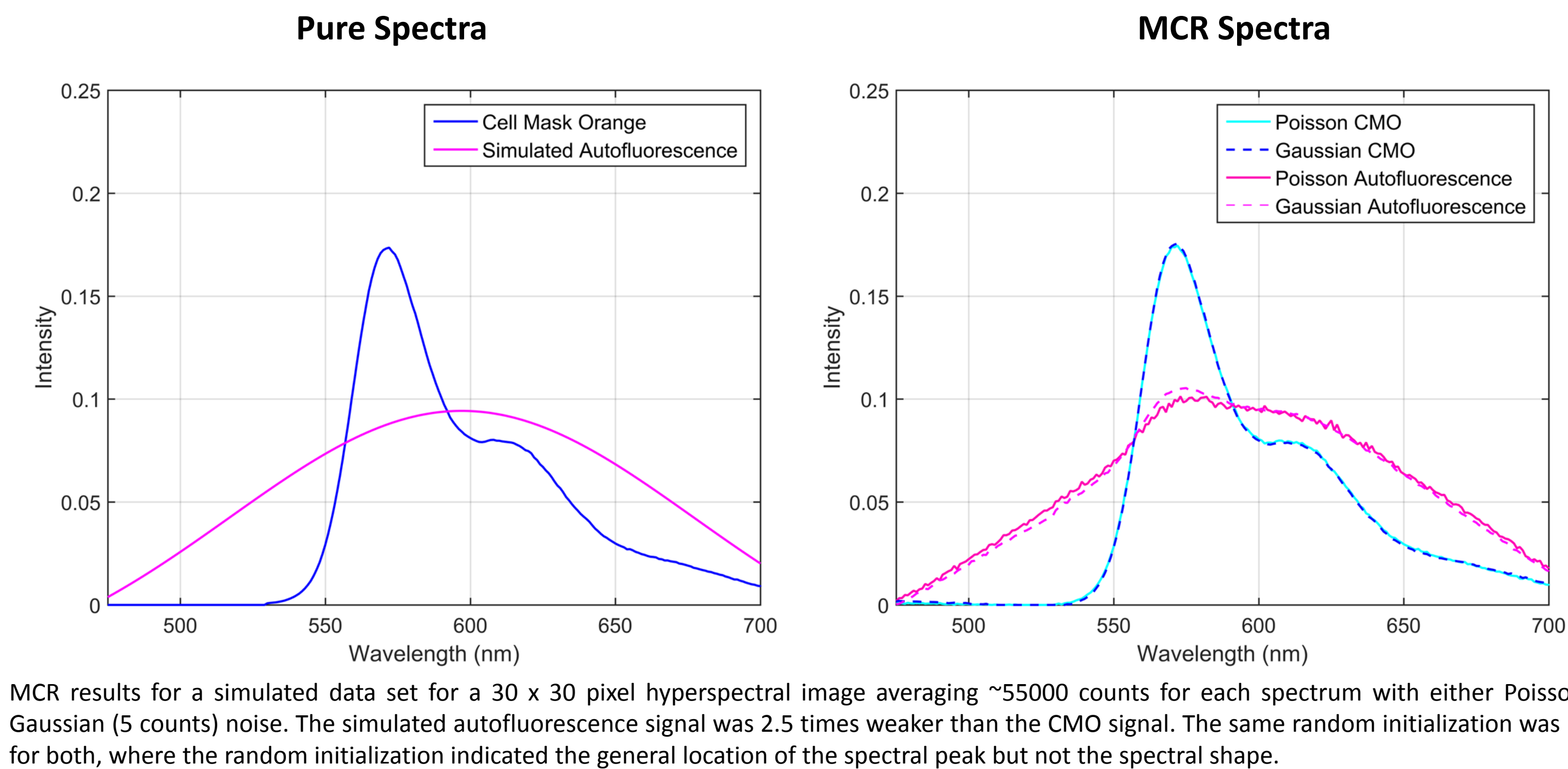
Mathematical isolation of independently varying chemical species is accomplished using a fast multivariate curve resolution algorithm with robust constraints.³ Example shown: hyperspectral confocal⁴ (not STED) imaging of endogenous pigments in cyanobacterium *Cyanothece*

Rotational Ambiguity



The MCR algorithm is deterministic, producing a unique output for a given set of inputs. However, if the pure spectra are not known *a priori* and the spectra must be randomly initialized, the algorithm will produce a range of outputs which depend upon the random initialization. The observed range of outputs indicates remaining rotational ambiguity as well as possible trapping of the optimization in local rather than global minima. Alternate optimization schemes are being explored to avoid becoming trapped by local minima. Separately, the remaining rotational ambiguity is being evaluated and the uncertainty quantified.

Wavelength Dependent Noise



Typically, MCR algorithms assume that the noise is independent and ideally distributed (i.e. Gaussian white noise). In the presence of noise violating this assumption, such as the simulated Poisson noise above, leads to over-fitting where part of the noise becomes embedded in the spectral model. In a separate issue, when MCR determines the spectra of weaker components, often some of any stronger spectra will be mixed with it.

Conclusions

Multivariate Curve Resolution is a valuable tool for the analysis of hyperspectral images, allowing the recovery of the number of different spectral components, their pure spectra, and their spatial distribution with minimal *a priori* knowledge. However, interpretation of the results can be complicated, where some areas of potential improvement are highlighted.

Acknowledgements

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References

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