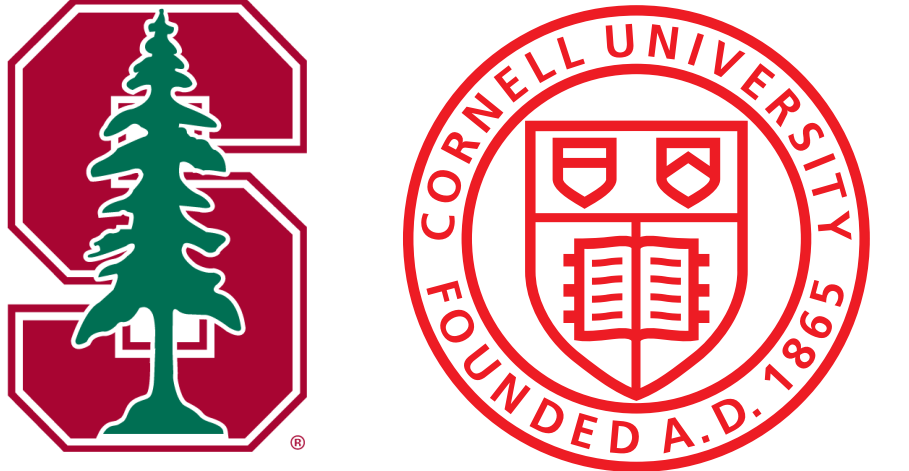


Blind Source Separation Algorithms for PSF Subtraction from Direct Imaging

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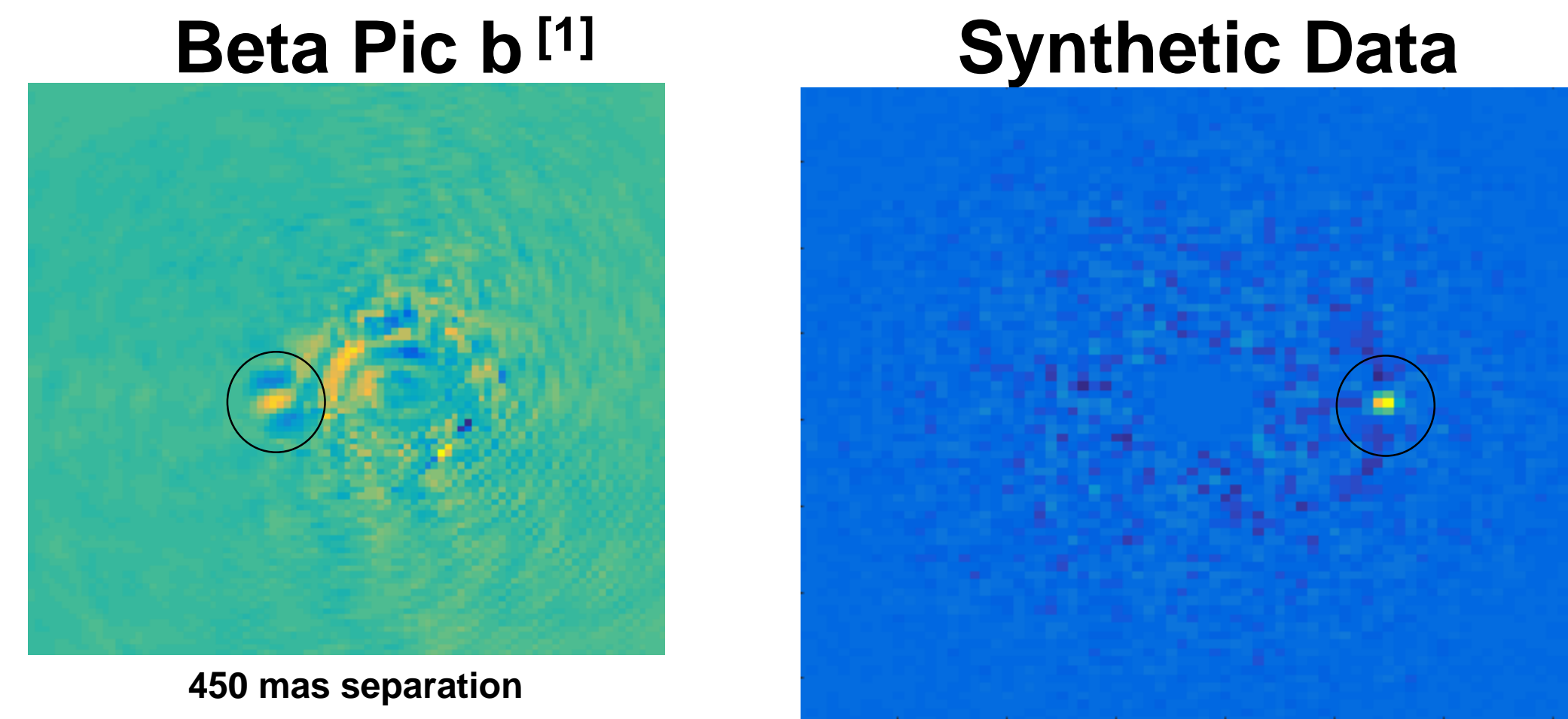


Introduction

Direct Imaging is the search for exoplanets by observing their star with a coronagraph. Unfortunately, the target signal of the planet is a similar order of magnitude to that of the noise sources.

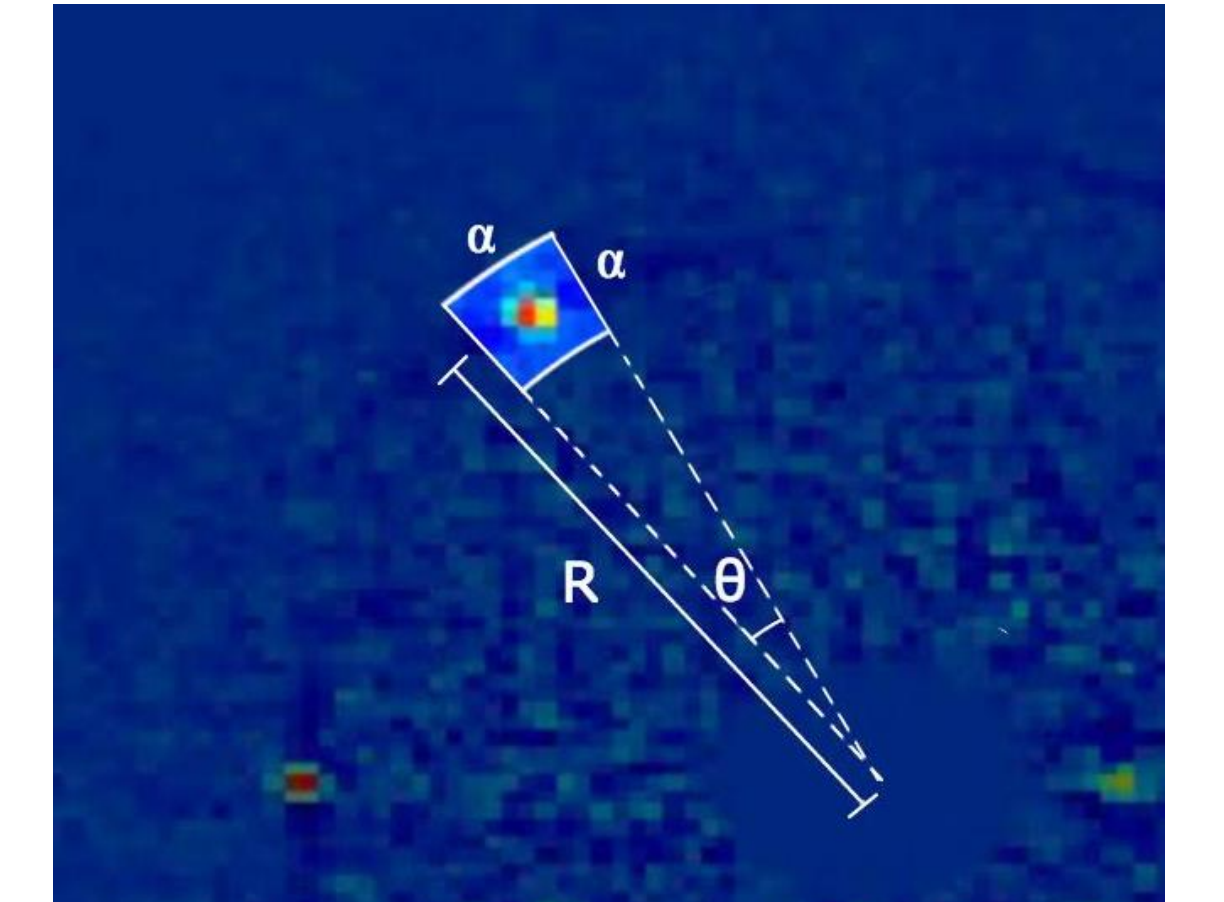
This research examines the effects and biases of algorithms designed to separate the planet signal from the noise sources. These algorithms induce both astrometric and photometric biases. Each method addressed here is compared to KLIP^[2], a popular variant of the current standard, Principal Component Analysis.

KLIP Reduced



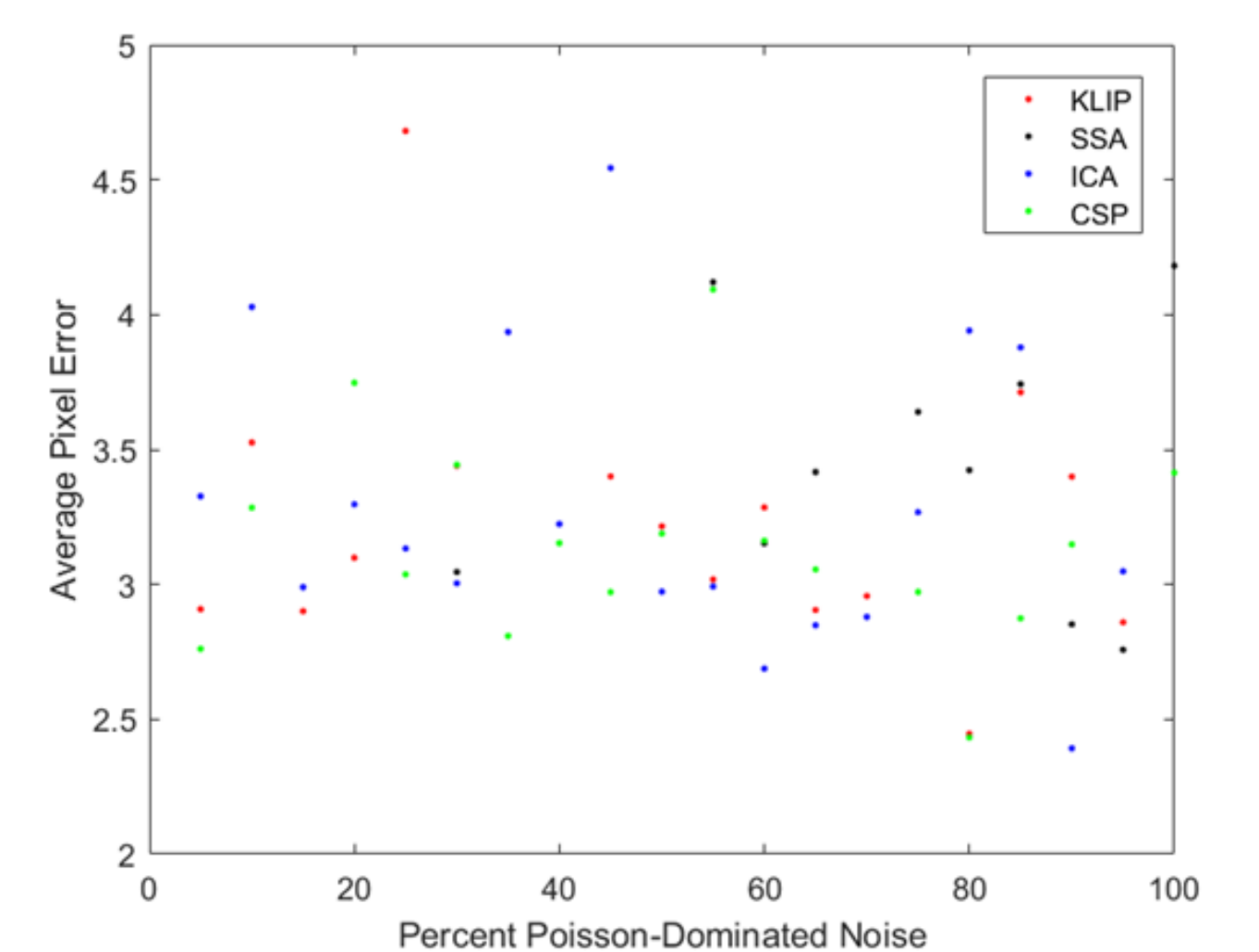
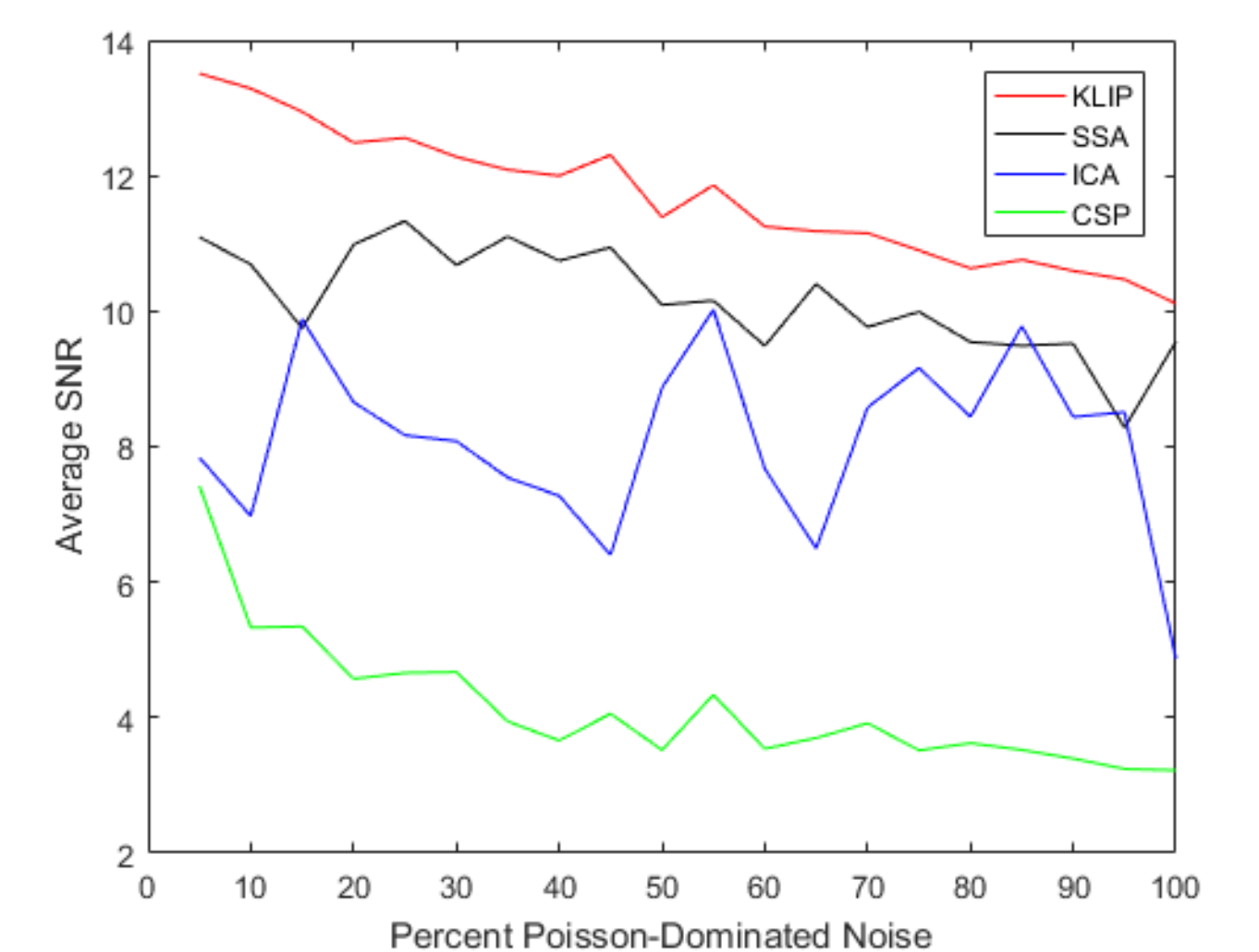
Metrics

- Astrometric Error
- Signal to Noise Ratio



$\alpha = 2 \times \text{FWHM of planet signal}$, $\theta = 2 \times \text{FWHM of star PSF}$, $R = \text{pixel distance between planet signal and center of star PSF}$

Conclusions



- Each method performs worse as the data is more Poisson and read-noise dominant.
- No astrometric error correlations (across neither methods nor noise type). None of the Pearson Correlation Coefficients are greater than 0.22. Likely improved by using forward model matched filters instead of Gaussian fits.
- No methods outperform KLIP, but they do perform at a similar order of magnitude, and often with quicker computation times.

Acknowledgements

This work is supported by NASA Grant No. NNX16AI13G.

Based on observations obtained at the Gemini Observatory, which is operated by the Association of Universities for Research in Astronomy, Inc., under a cooperative agreement with the National Science Foundation (NSF) on behalf of the Gemini partnership: the NSF (United States), the National Research Council (Canada), CONICYT (Chile), the Australian Research Council (Australia), Ministério da Ciência, Tecnologia e Inovação (Brazil), and Ministerio de Ciencia, Tecnología e Innovación Productiva (Argentina).

References

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Independent Component Analysis

Overview

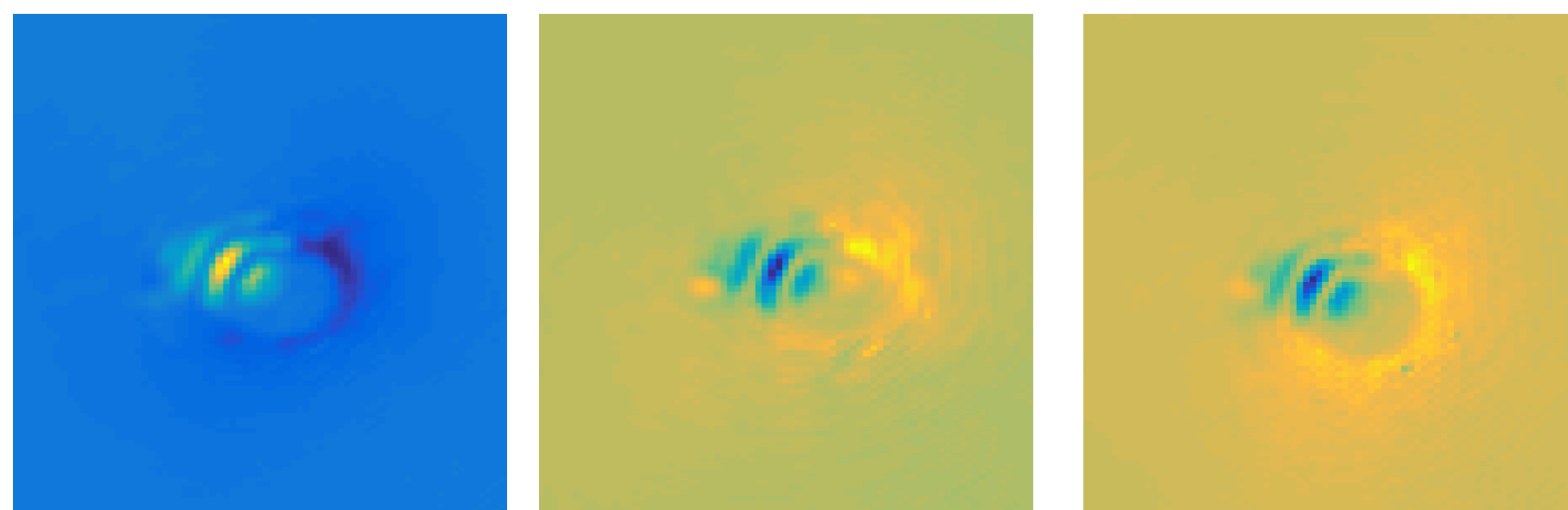
Assume all data is a combination of multiple independent data sources:

$$x = As$$

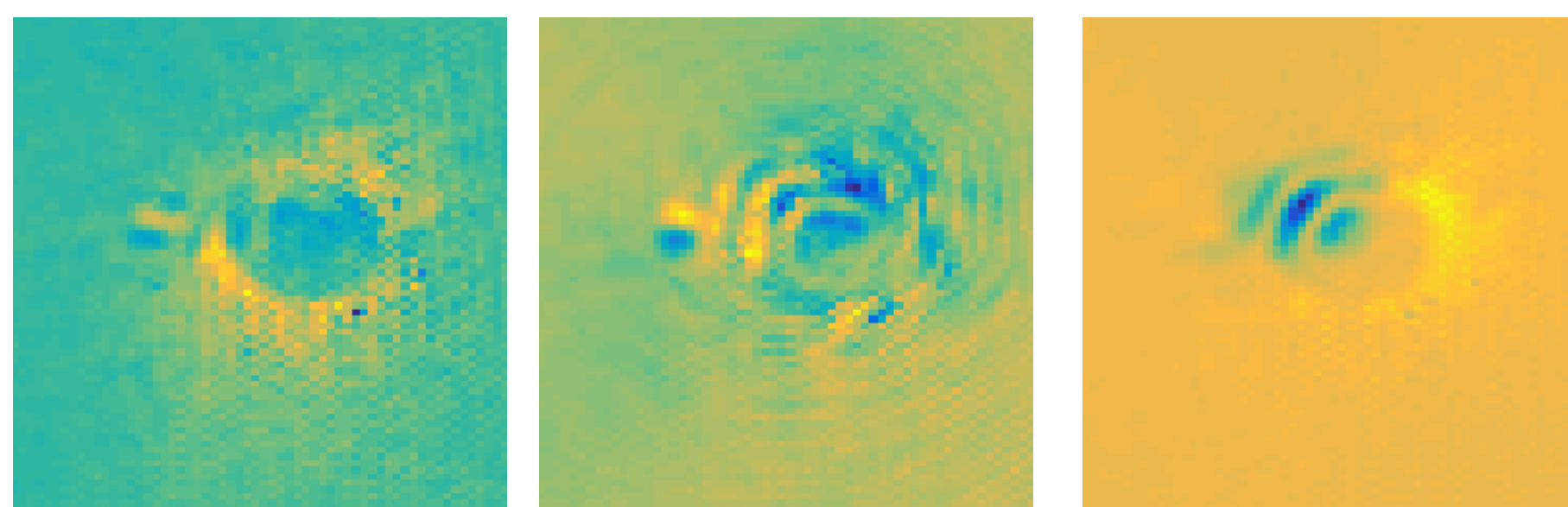
Based on the Central Limit Theorem, to be independent the sources must not be Gaussian. Find an A that maximizes the nongaussianity of s . The reproduction of s is signless and scale-less^[3].

Applied Methodology

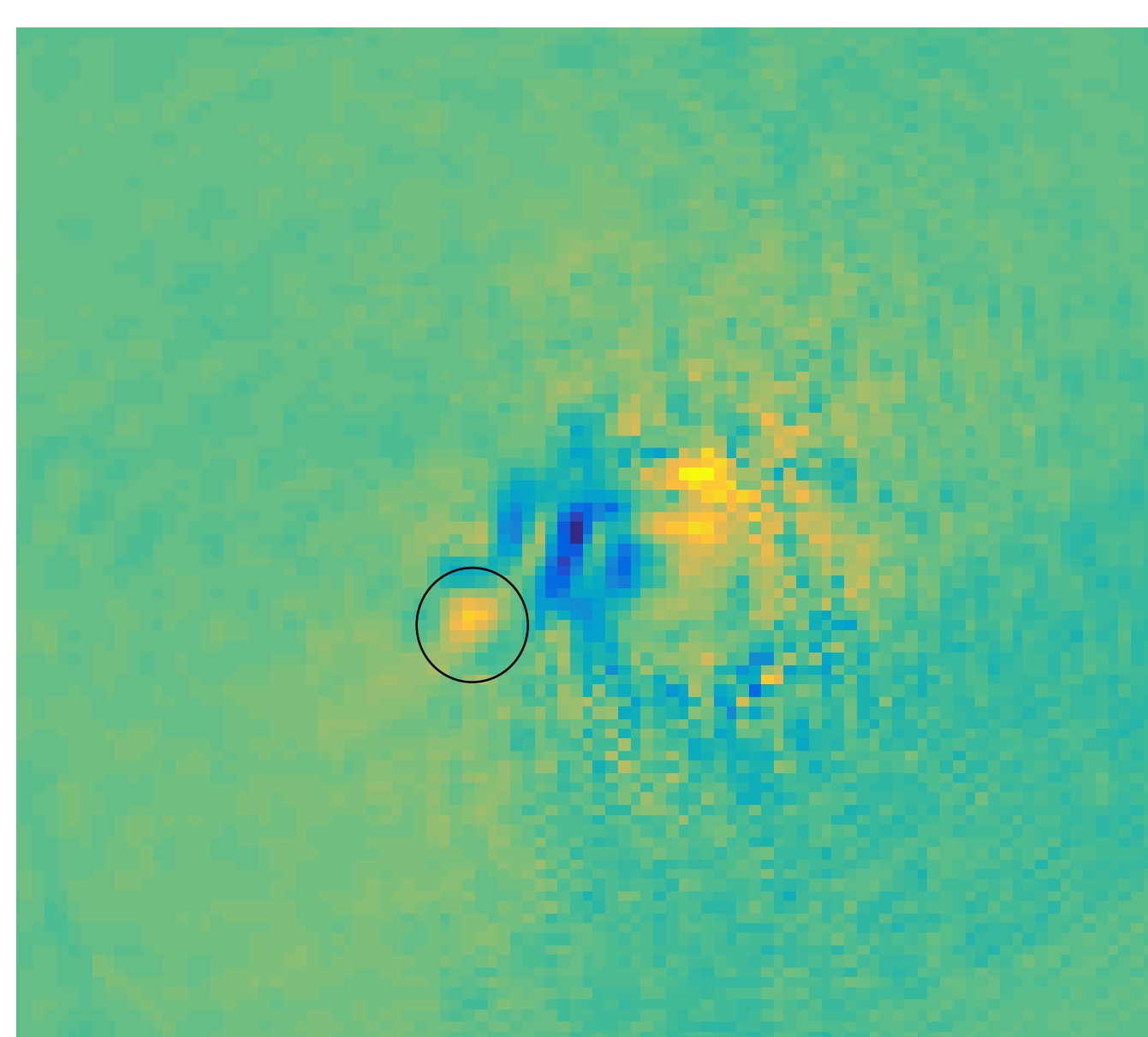
- Do a KLIP analysis of the data. Instead of derotating and stacking all images, do so in 3 bins:



- Conduct ICA on those 3 images:



- Optimally derotate and stack images:



Stationary Subspace Analysis

Overview

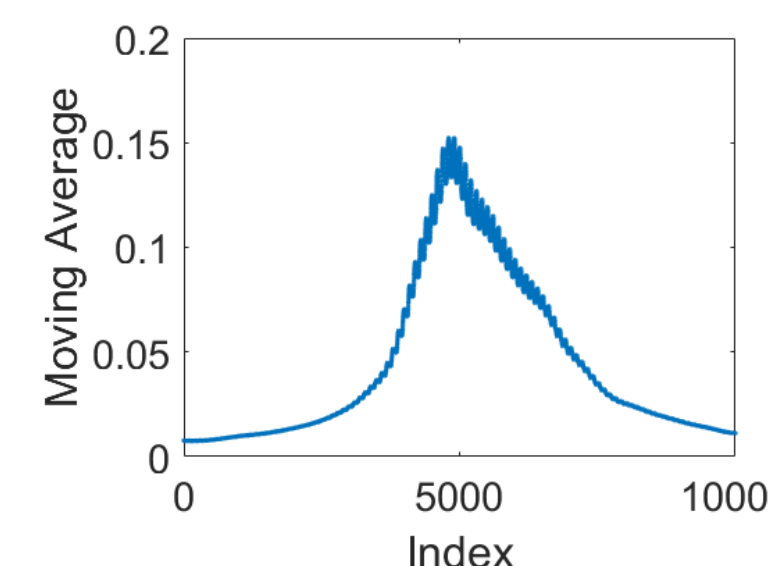
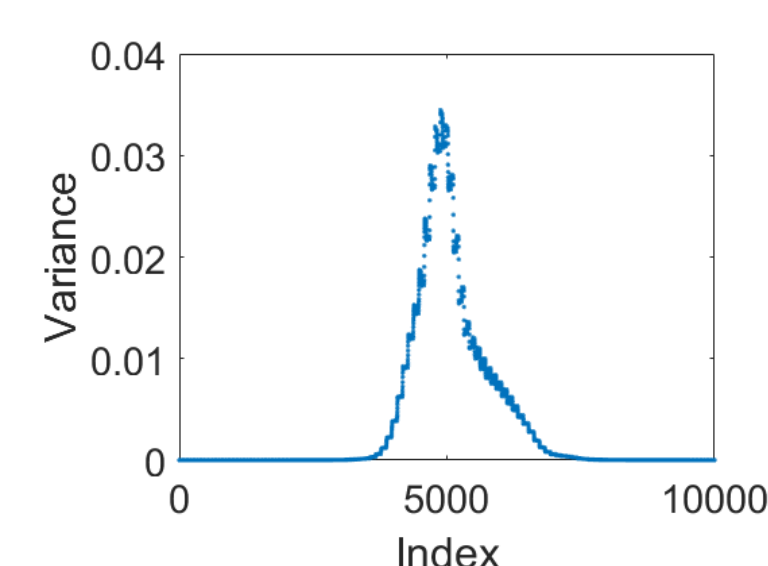
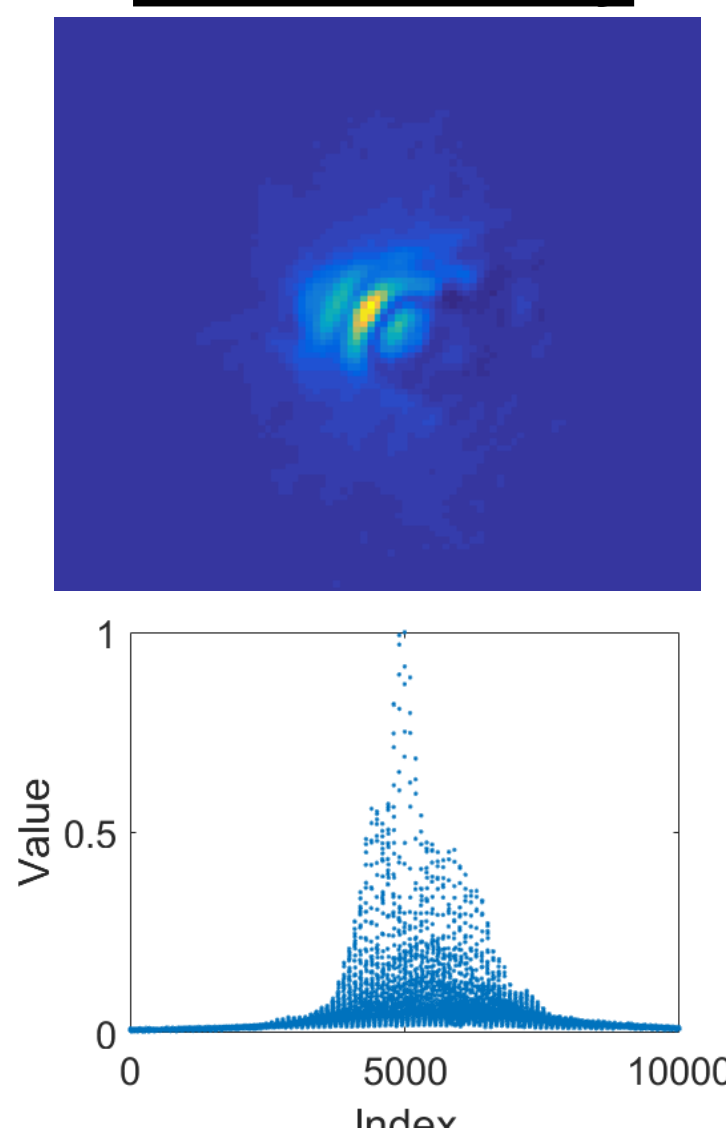
SSA seeks to separate signals that have a constant distribution (stationary), and those that do not. Assume m stationary sources^[4].

$$x(t) = As(t) = [A^s \ A^n] \begin{bmatrix} s^s(t) \\ s^n(t) \end{bmatrix}$$

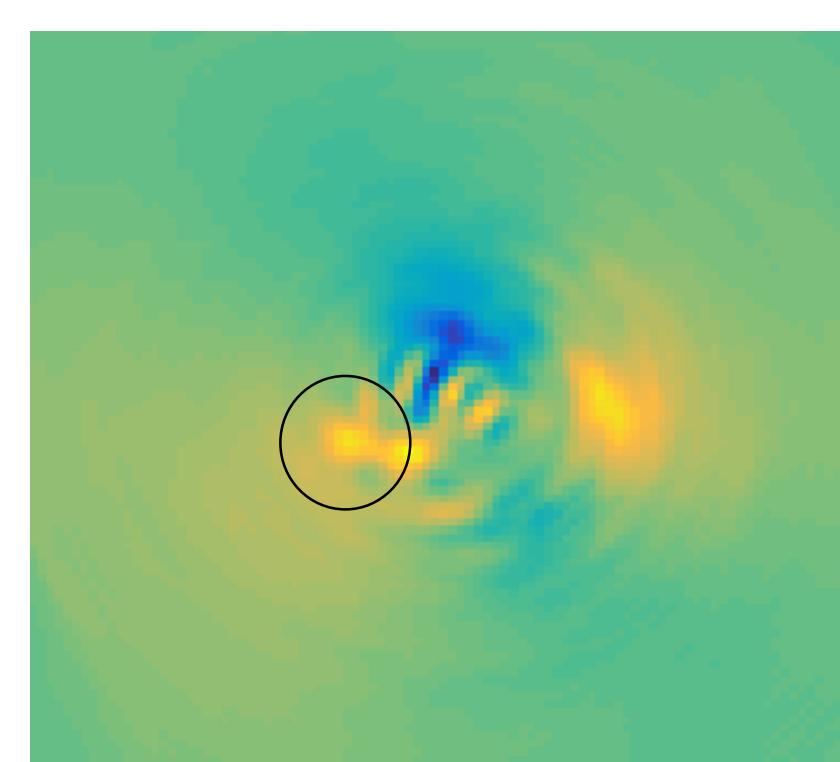
Applied Methodology

- Let each vectorized image be a spatial signal.
- Subtract each component with "structure" from the image. These are seen as nonstationary:

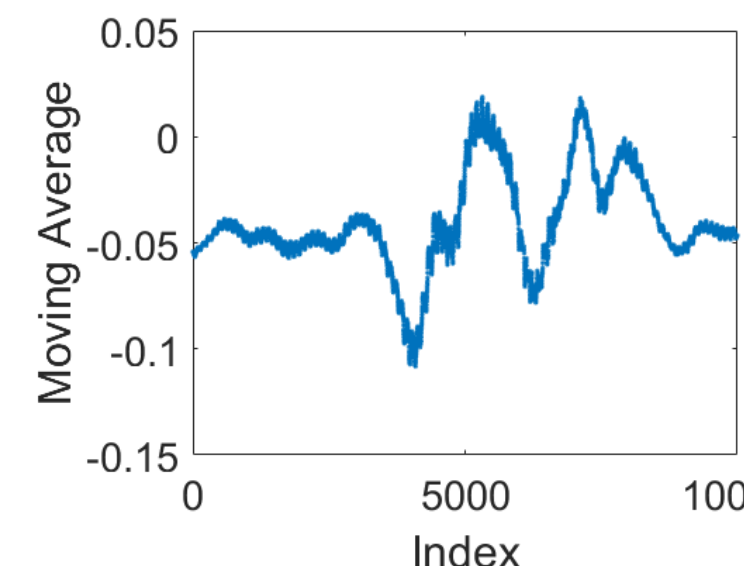
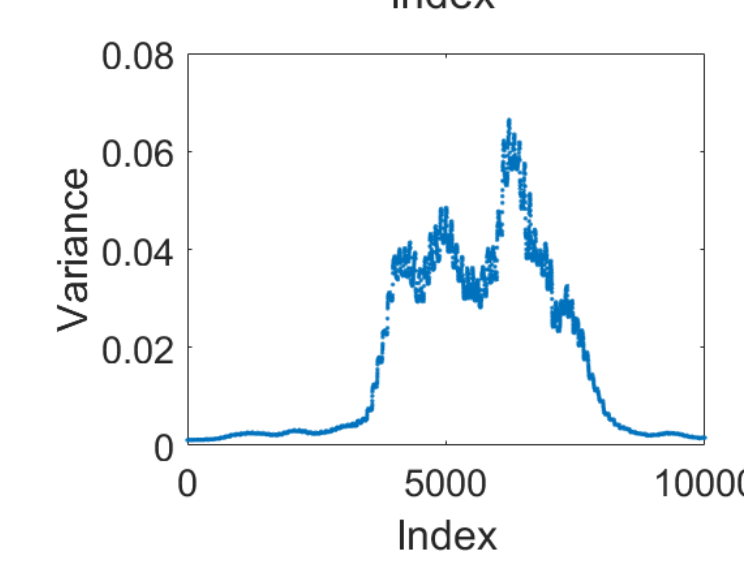
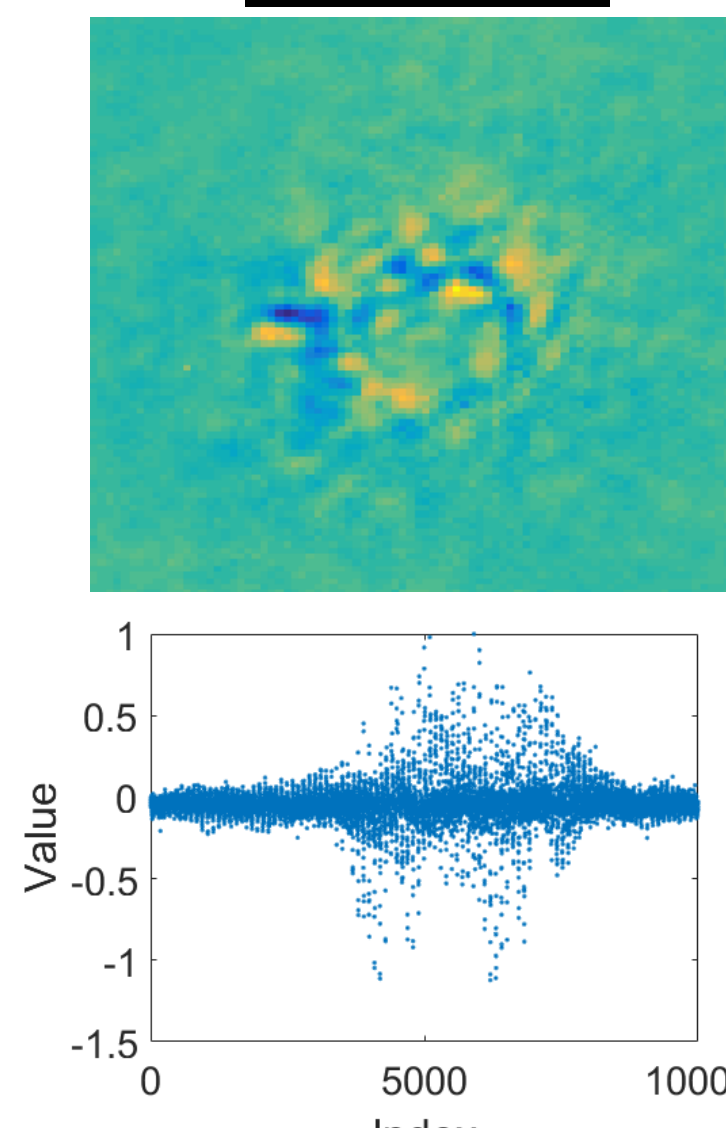
Nonstationary



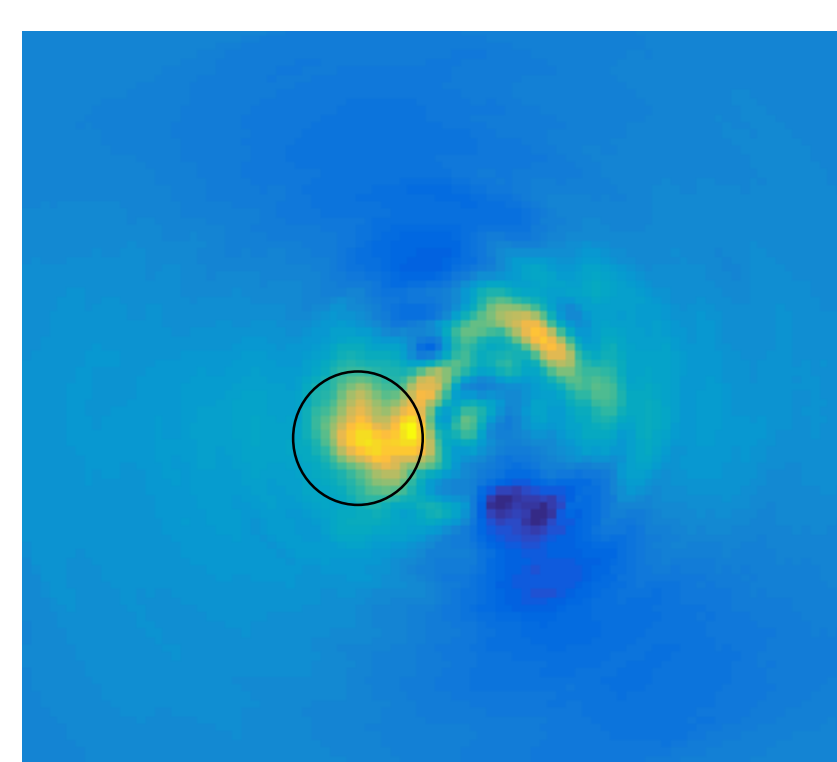
$m = 3$



Stationary



$m = 10$



Common Spatial Pattern Filtering

Overview

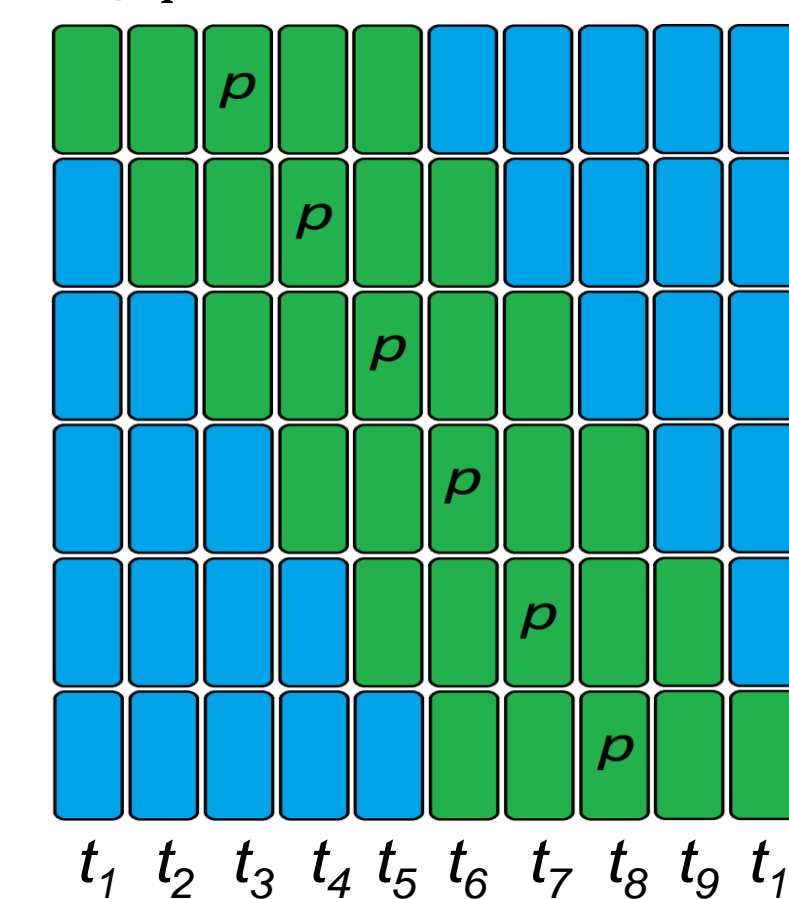
Find a coordinate transformation that maximizes the difference between two distributions^[5]:

$$w = \underset{w}{\operatorname{argmax}} \frac{\|wX_1\|^2}{\|wX_2\|^2}$$

Applied Methodology

The goal is to find the transformation that maximizes the difference between images with the planet signal clustered together compared to those where it is far away. The maximum projection should be the planet signal.

- Divide the dataset in half chronologically, with X_1 centered on a target image p .
- For images taken at n different times, $n/4 < p < 3n/4$



- Find w for each p .
- For each analysis, $G = \begin{bmatrix} (w^T w)X_1 \\ -(w^T w)X_2 \end{bmatrix}$
- Unpack each row of G into an image, derotate, and stack.
- Repeat for all possible p , and stack.
- Can also be extended into SDI by using nearby wavelengths in X_1 .

