

Sparse Modeling for Radio Interferometry

— Basics, Applications and its Current Status —

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(NRAO Jansky Fellow / MIT Haystack Observatory)

On behalf of Many On-going Research Projects related to Sparse Modeling

Developer Team: Shiro Ikeda (ISM), Fumie Tazaki (NAOJ), Kazuki Kuramochi (U Tokyo), Mahito Sasada (NAOJ), Mareki Honma (NAOJ), CASA Developer Team (Nakazato et al., NAOJ)

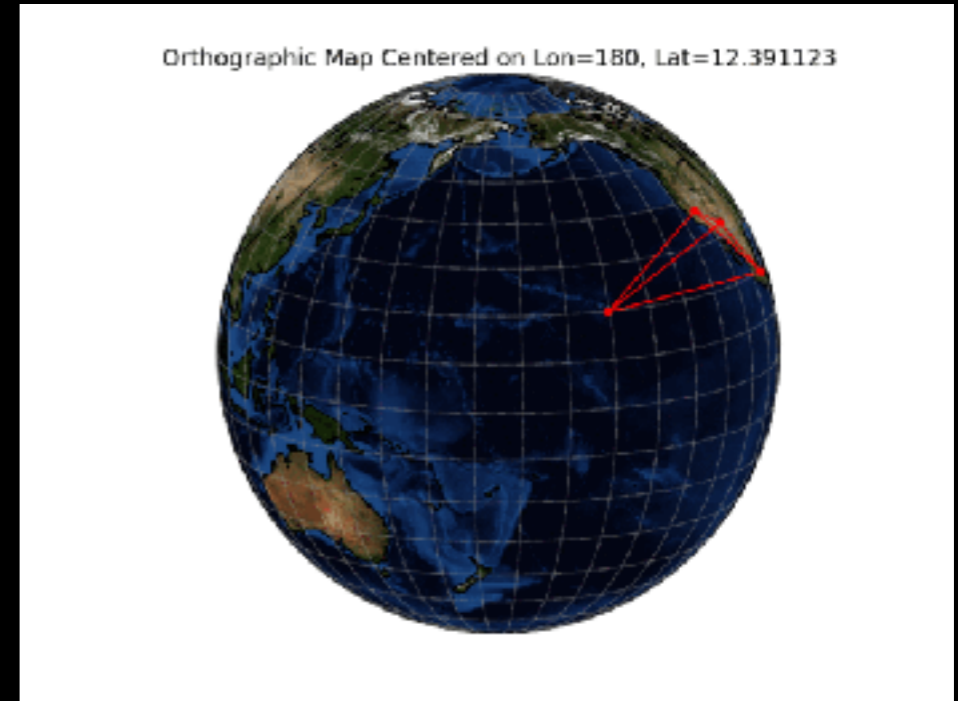
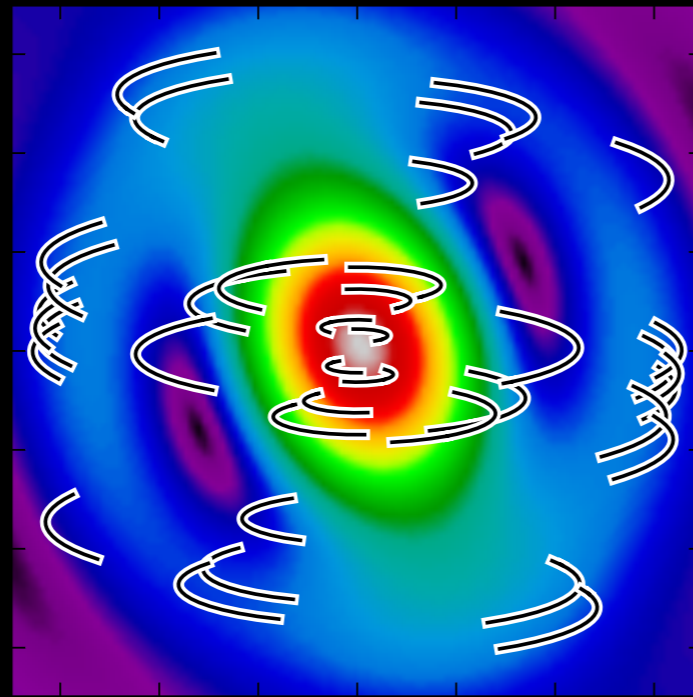
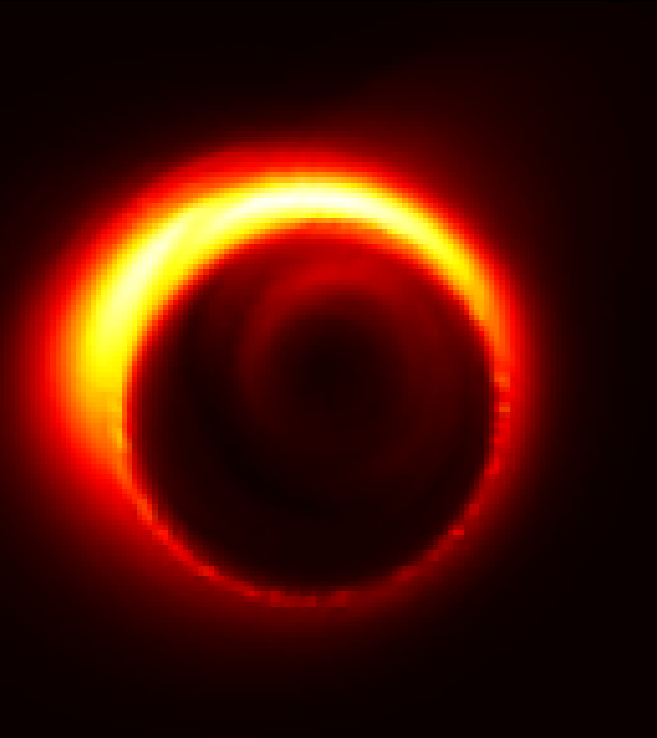
Collaborators: Masayuki Yamaguchi (NAOJ), Akimasa Kataoka, Ryohei Kawabe, et al. Lynn Mathews, EHT Imaging Working Group et al. Takuya Akahori, Ketaro Takahashi, SKA Faraday Tomography WG,

Radio Interferometry: Sampling Fourier Components of the Images

Image

Fourier Domain
(*Visibility*)

Sampling Process
(Projected Baseline = Spatial Frequency)



(Images: adapted from [Akiyama et al. 2015, ApJ](#) ; Movie: Laura Vertatschitsch)

Sampling is **NOT** perfect

Interferometry Imaging: Observational equation is *ill-posed*

$$\begin{array}{c}
 \mathbf{Y} \\
 \text{(Data)}
 \end{array}
 =
 \begin{array}{c}
 \mathbf{A} \\
 \text{(Fourier Matrix)}
 \end{array}
 \begin{array}{c}
 \mathbf{X} \\
 \text{(Image)}
 \end{array}$$

$$\begin{pmatrix}
 y_1 \\
 y_2 \\
 y_3 \\
 \vdots \\
 y_M
 \end{pmatrix}$$

$$=
 \begin{pmatrix}
 \exp(i2\pi u_1 x_1) & \exp(i2\pi u_1 x_2) & \dots & \exp(i2\pi u_1 x_N) \\
 \exp(i2\pi u_2 x_1) & \exp(i2\pi u_2 x_2) & \dots & \exp(i2\pi u_2 x_N) \\
 \exp(i2\pi u_3 x_1) & \exp(i2\pi u_3 x_2) & \dots & \exp(i2\pi u_3 x_N) \\
 \vdots & \vdots & \vdots & \vdots \\
 \exp(i2\pi u_M x_1) & \exp(i2\pi u_M x_2) & \dots & \exp(i2\pi u_M x_N)
 \end{pmatrix}$$

$$\begin{pmatrix}
 x_1 \\
 x_2 \\
 x_3 \\
 \vdots \\
 x_N
 \end{pmatrix}$$

- Sampling is NOT perfect
Number of data M < Number of image pixels N
- Equation is *ill-posed*: infinite numbers of solutions
- Interferometric Imaging:
Picking a reasonable solution based on a prior assumption

Sparse Reconstruction: A Popular Approach

Philosophy: Reconstructing images with the smallest number of point sources within a given residual error

Computationally very expensive!!
(It can be solved for $N < \sim 100$)

- L_0 norm is not continuous, nondifferentiable
- Combinational Optimization

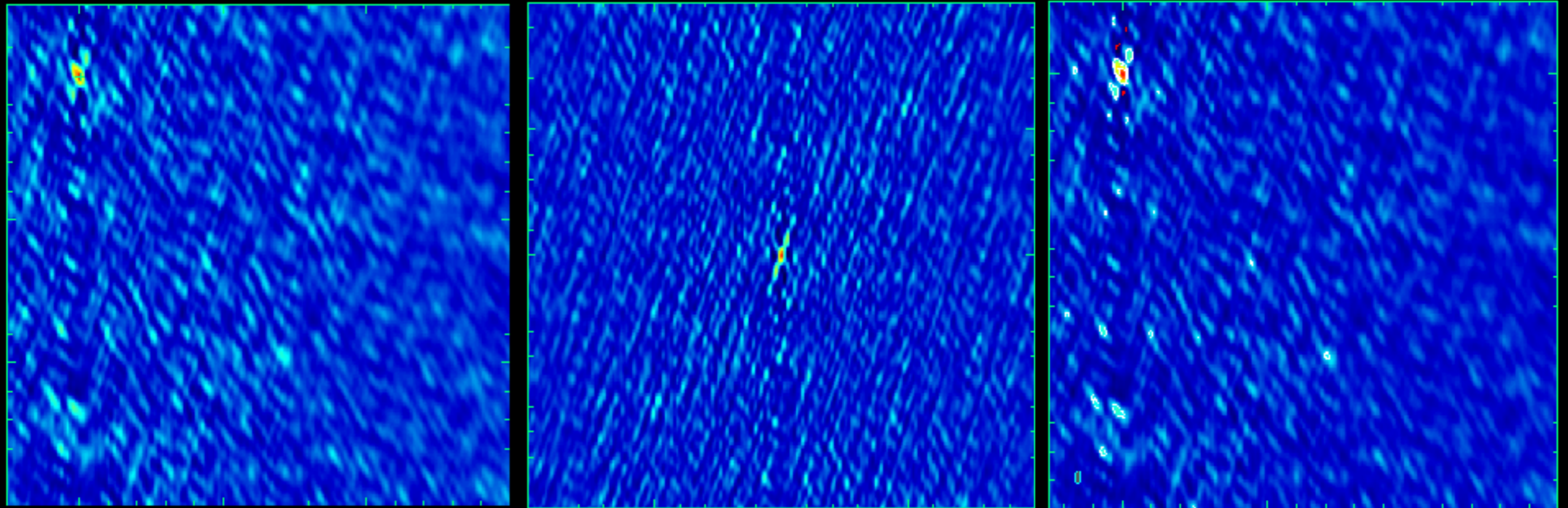
$\|\times\|_0 =$ number of non-zero pixels in the image



Sparse Reconstruction: CLEAN (greedy approach)

CLEAN (Hobgorn 1974) = Matching Pursuit (Mallet & Zhang 1993)

Computationally very cheap, but highly affected by the Point Spread Function



Dirty map:

FT of zero-filled
Visibility

Point Spread Function:

Dirty map
for the point source

Solution:

Point sources
+ Residual Map

(3C 273, VLBA-MOJAVE data at 15 GHz)



Event Horizon Telescope

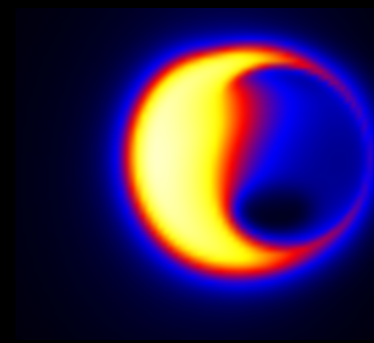
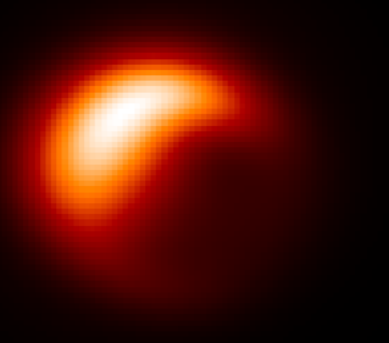


Sparse Reconstruction: CLEAN (greedy approach)

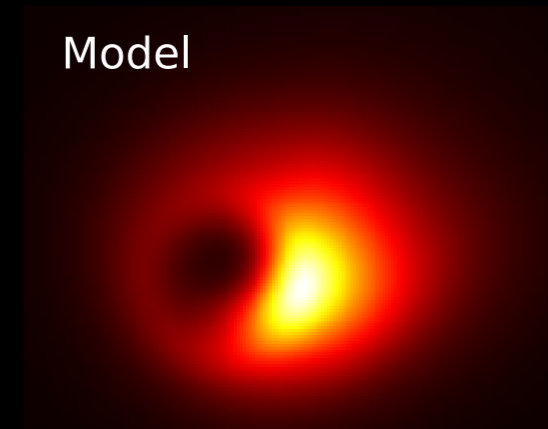
CLEAN (Hobgorn 1974) = Matching Pursuit (Mallet & Zhang 1993)

CLEAN is problematic for the black hole shadows?

Ground Truth



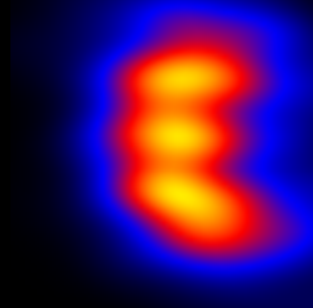
Model



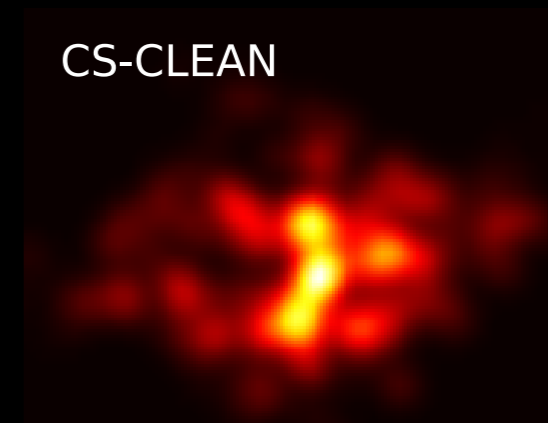
CLEAN



CLEAN



CS-CLEAN



Fabian Baron,
EHT 2012

Chael+2016 ApJ

Akiyama+2017a, ApJ
Akiyama+2017b, AJ



Sparse Reconstruction: L1 Regularization

LASSO (Tibshirani 1996)

Convex Relaxation: Relaxing L0-norm to a convex, continuous, and differentiable function

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 < \varepsilon$$



equivalent

$$\min_{\mathbf{x}} \left(\underbrace{\|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2}_{\text{Chi-square}} + \underbrace{\Lambda_l \|\mathbf{x}\|_1}_{\text{Regularization on sparsity}} \right).$$

Chi-square

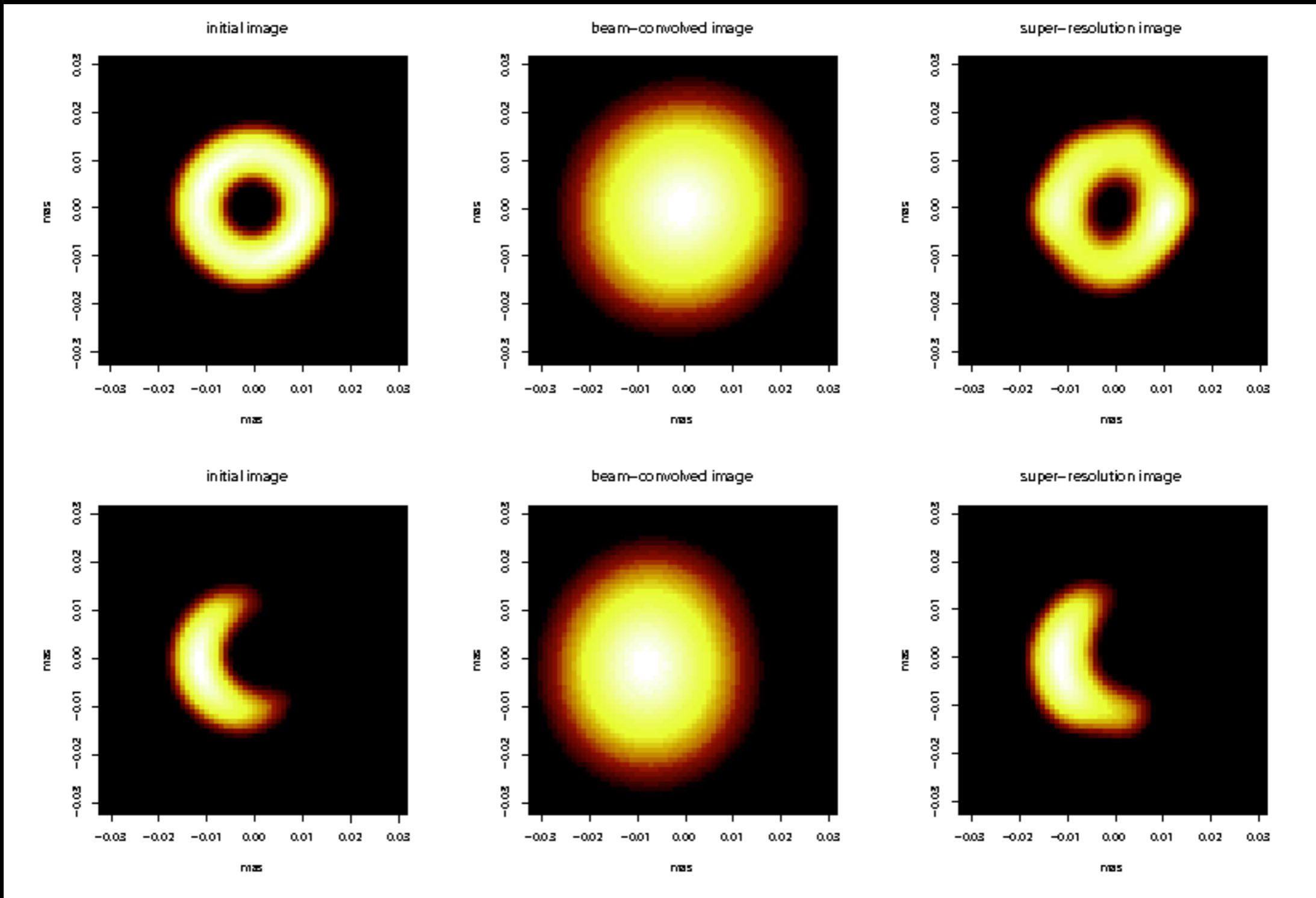
Regularization
on *sparsity*

- Reconstruction purely in the visibility domain:
 - Not affected by de-convolution beam (point spread function)
- Many applications after appearance of *Compressed Sensing* (Donoho, Candes+)

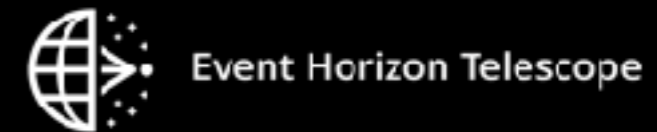


Event Horizon Telescope

Sparse Reconstruction: L1 Regularization LASSO (Tibshirani 1996)



(Honma, *Akiyama*, Uemura & Ikeda 2014, PASJ)



Note: A “Popular” Wrong Statement



Imaging techniques can provide the perfect reconstruction if we have an infinite SNR (i.e. no noises) on data.

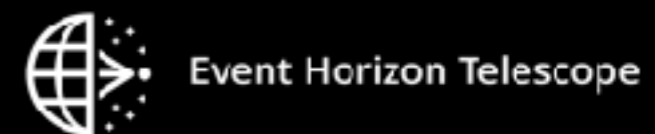
They can achieve even infinite angular resolutions in this case.

Interferometric Imaging:

- *Regardless of noises*, we have a infinite number of solutions fitting data
- It just picks a reasonable solution based on a prior assumption

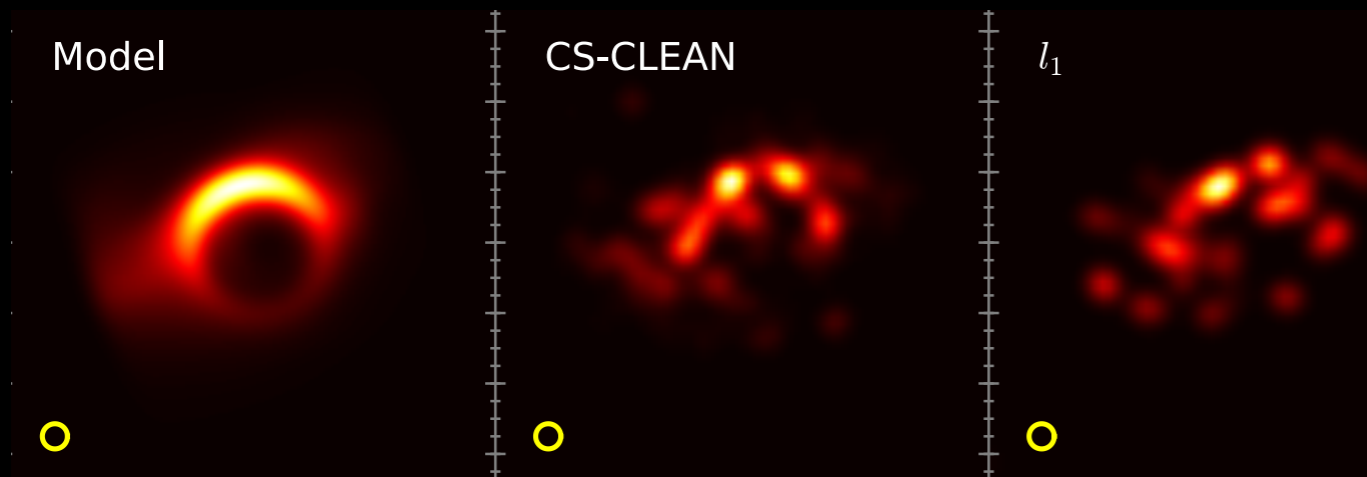
If the prior assumption is wrong, images can be wrong.

The angular resolution limit to distinguish 2 discrete sources from 1 source
~ $0.25 \lambda/D$ (no noises; Narayan & Nityananda 1986
with noises; Honma et al. 2014, PASJ and many other papers)



Pursuing only sparsity is not optimal

A key assumption in CLEAN and L1 regularization: images must be sparse.



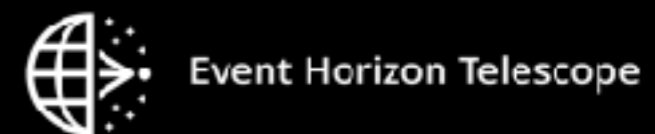
May NOT work!

- Extended source
- Even compact source with too small image pixels

Akiyama et al. 2017b, AJ



We need somewhat sparse and smooth images
NOT depending on adopted sizes of imaging pixels.



Sparse Modeling on the Gradient Image

$$\min_{\mathbf{x}} \left(\underbrace{\|y - \mathbf{A}\mathbf{x}\|_2^2}_{\text{Chisquare}} + \underbrace{\Lambda_l \|\mathbf{x}\|_1}_{\text{L1 norm}} + \underbrace{\Lambda_t \|\mathbf{x}\|_{\text{tv}}}_{\text{Total Variation:}} \right)$$

Chisquare

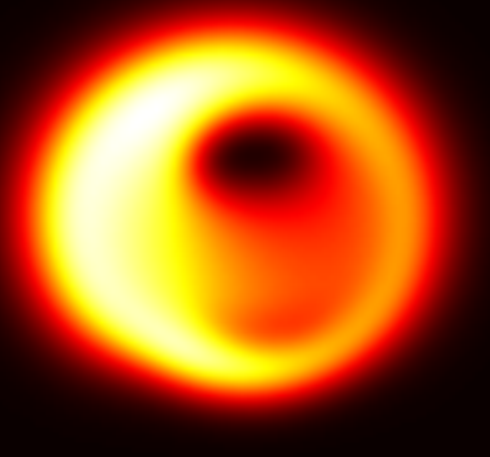
L1 norm

Total Variation:

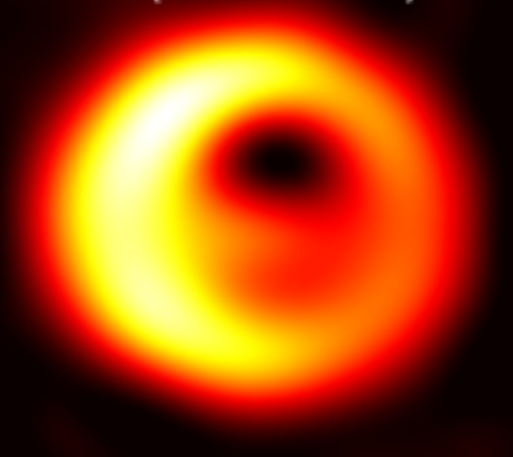
Regularizing the *sparsity on the gradient domain*
= Favoring smooth images

$$\|\mathbf{x}\|_{\text{tv}} = \sum_i \sum_j \left(|x_{i+1,j} - x_{i,j}|^2 + |x_{i,j+1} - x_{i,j}|^2 \right).$$

Model



mfista (L1+TV^2)



Kuramochi et al. 2017
submitted to ApJ

Application to Real Data: Protoplanetary Disk

ALMA Observations of Protoplanetary Disk HD 142527 (345 GHz)

Compact configuration

Intermediate config.

Nominal Resolution

Superresolution (same to the intermediate configuration)

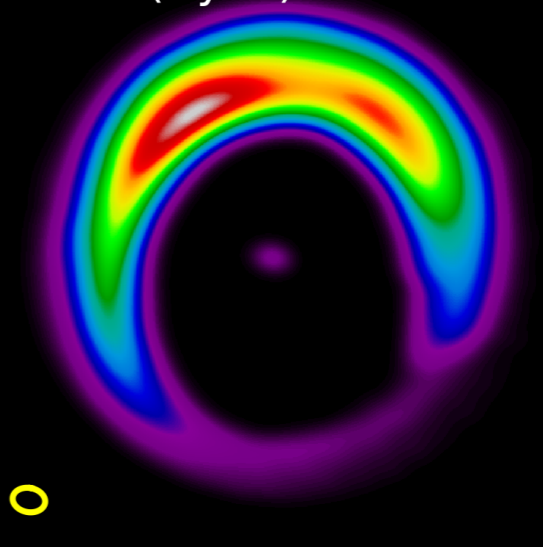
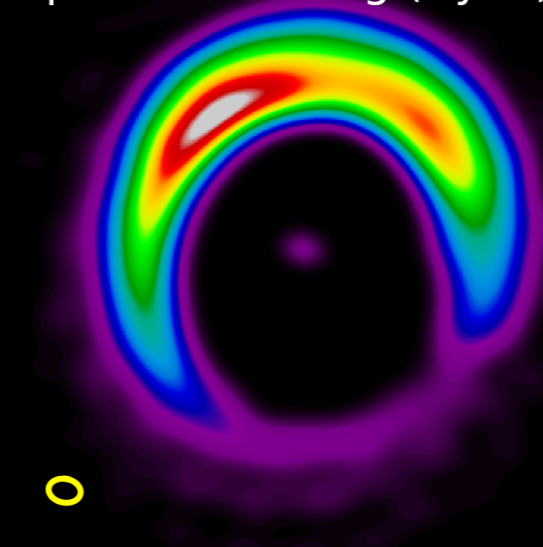
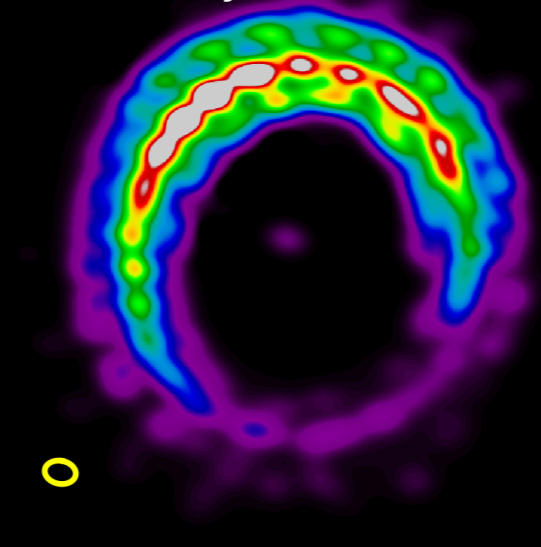
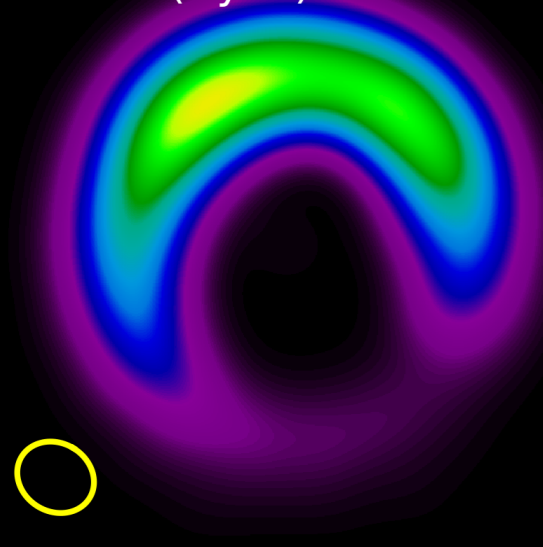
Nominal Resolution

CLEAN (Cyc3)

CLEAN (Cyc3)

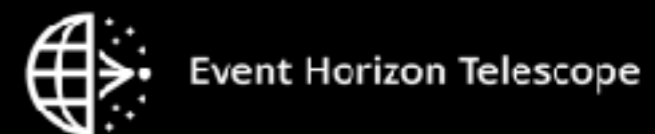
Sparse Modeling (Cyc3)

CLEAN (Cyc2)

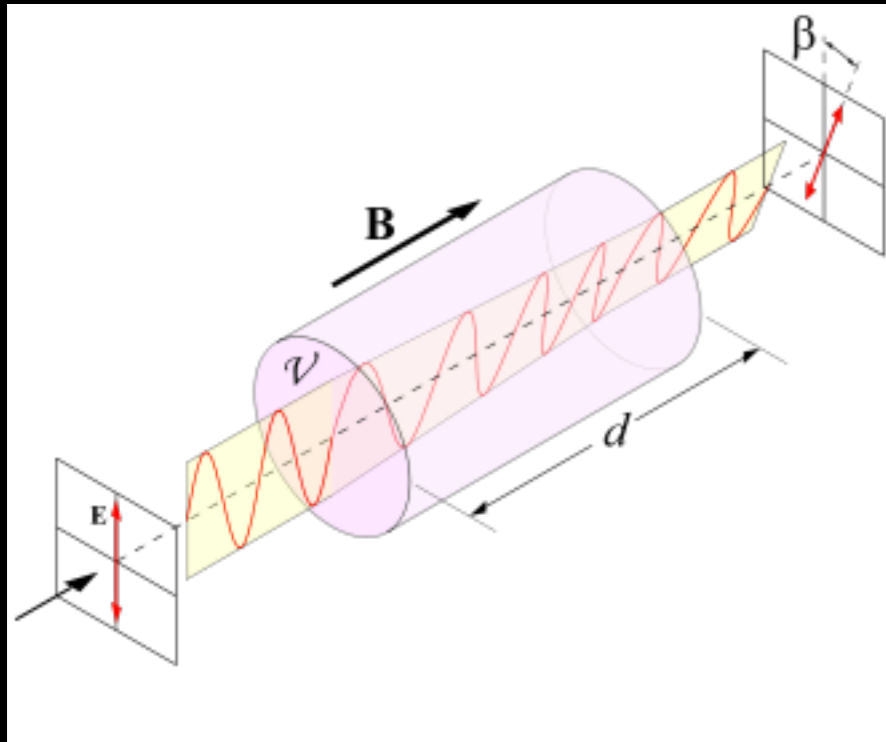


Kataoka et al. 2016, ApJ

Fukagawa et al. in prep.
(Yamaguchi, Akiyama, & Kataoka et al. in prep.)



Applications to SKA Science: Faraday Tomography



EVPA rotation of radio waves in magnetized plasma

$$\chi = \chi_0 + RM\lambda^2$$

$$RM \text{ (rad m}^{-2}\text{)} \approx 811.9 \int \left(\frac{n_e}{\text{cm}^{-2}} \right) \left(\frac{B_{\parallel}}{\mu\text{G}} \right) \left(\frac{dr}{\text{kpc}} \right)$$

Rotation angle is proportional to λ^2
 = phase rotation in linear Pol spectrum

This is very similar to what we usually see in interferometric data.

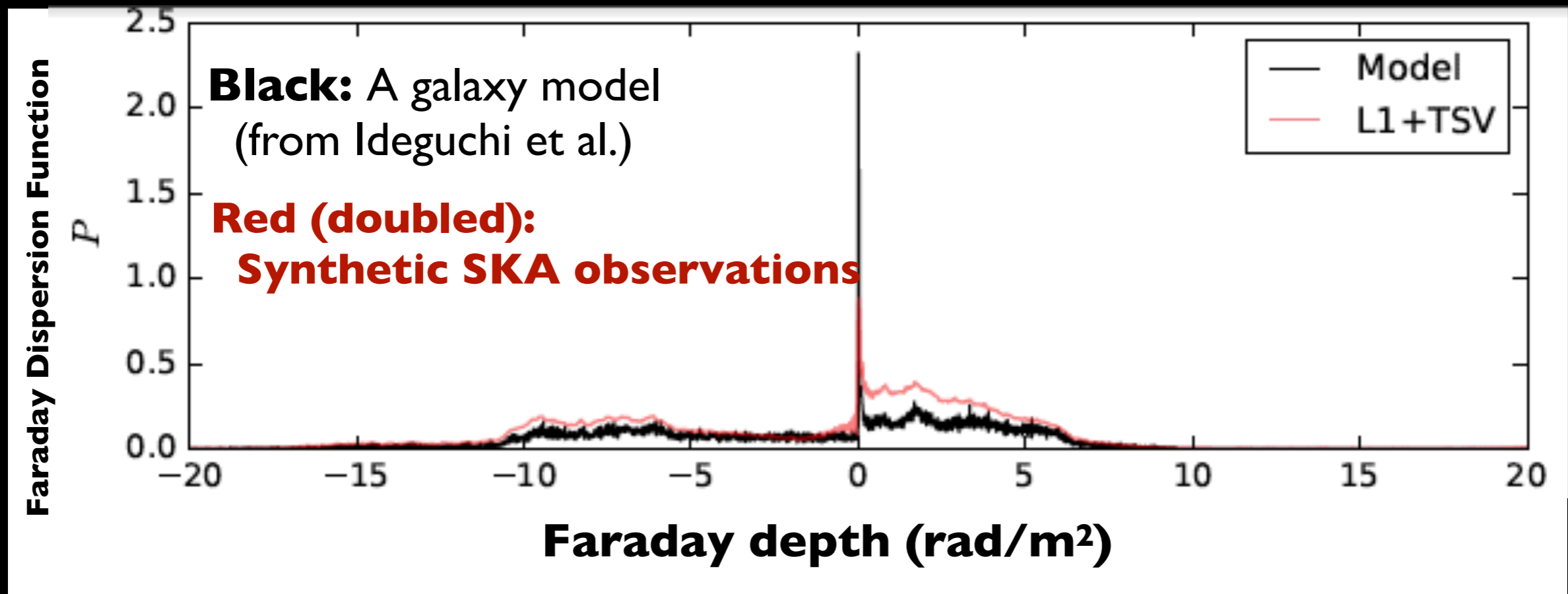
(e.g.) A point source in the image causes a phase rotation in the visibility, which is a spatial spectrum of the image.

$$\Delta\varphi = 2\pi\chi_0 u \quad \text{for a point source at } x = x_0$$

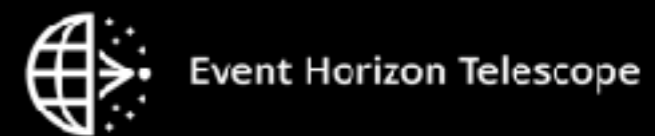
(x, u) for interferometric imaging; (RM, λ^2) for Faraday Rotation

Applications to SKA Science: Faraday Tomography

$$\begin{array}{ccc} \mathbf{Y} & = & \mathbf{A} \mathbf{X} \\ \text{Linear} & & \text{Fourier} & & \text{Fourier} \\ \text{Polarization} & & \text{Transform} & & \text{Dispersion} \\ \text{Spectra} & & \text{for Faraday depth} & & \text{Function} \end{array}$$



(Akiyama et al. in prep., Collaboration with SKA-JP Faraday Tomography WG)



EHT Imaging: Fusion of Young Powers & Divergence

Simulation

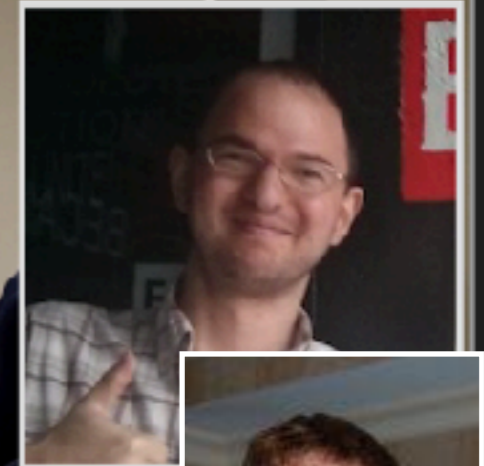
Andre Young
(SAO Astronomy)

Kazu Akiyama
(MIT Astronomy)

Julian Rosen
(UGA Mathematics)

Lindy Blackburn
(SAO Astronomy)

Katie Bouman
(MIT Computer Vision)



Michael Johnson
(SAO Astronomy)

Andrew Chael
(Harvard Physics)

Simulation

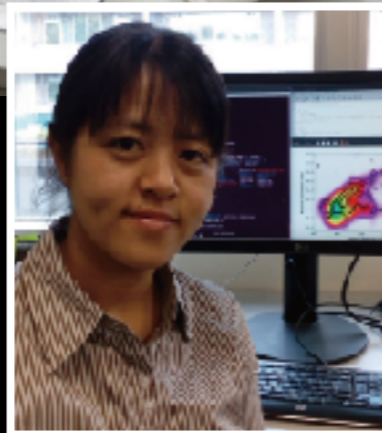
- An or
- Earth



Marki Honma
NAOJ
Astronomy



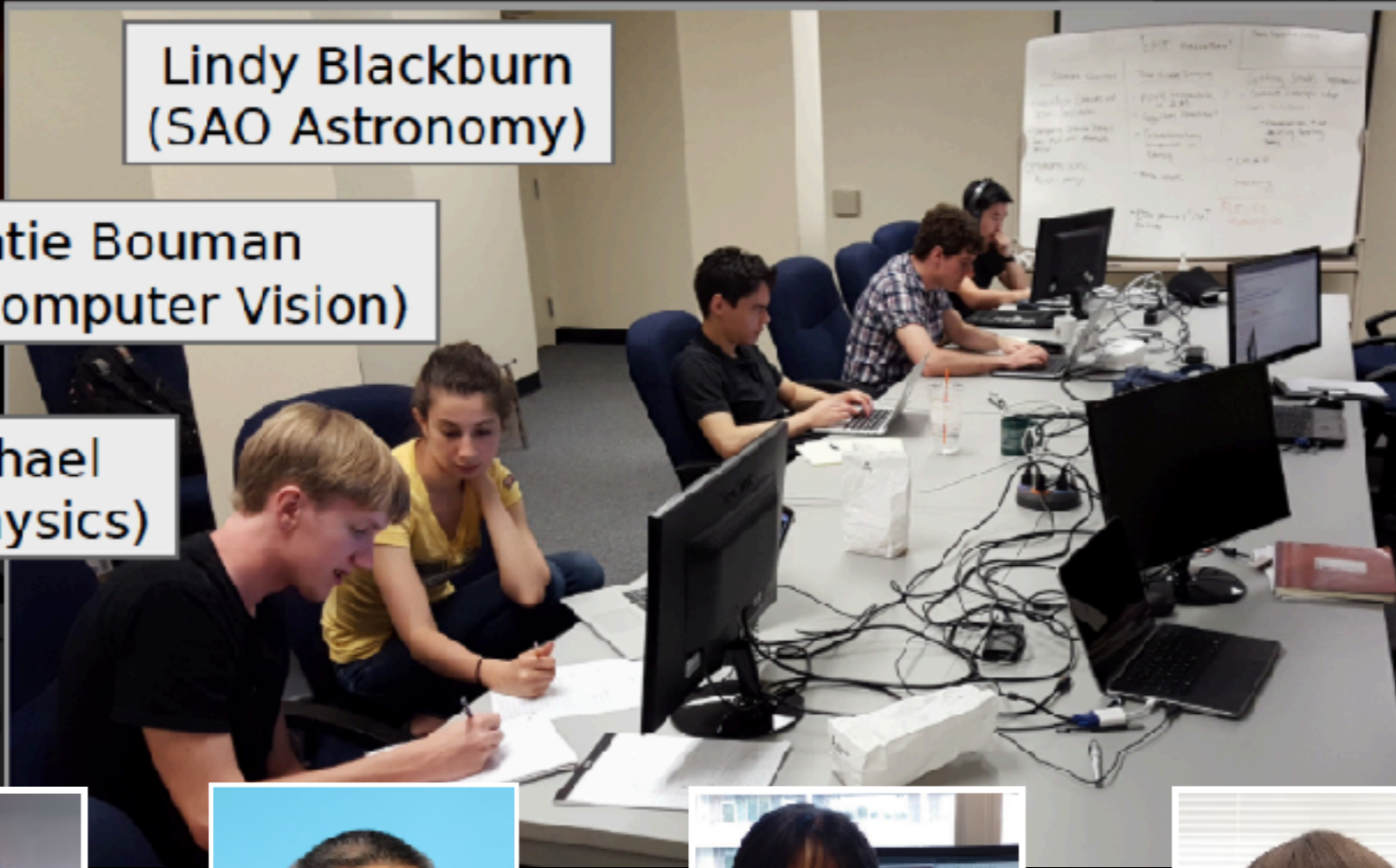
Shiro Ikeda
ISM Statistical
Mathematics



Fumie Tazaki
NAOJ Astronomy



Kazuki Kuramochi
U.Tokyo Astronomy



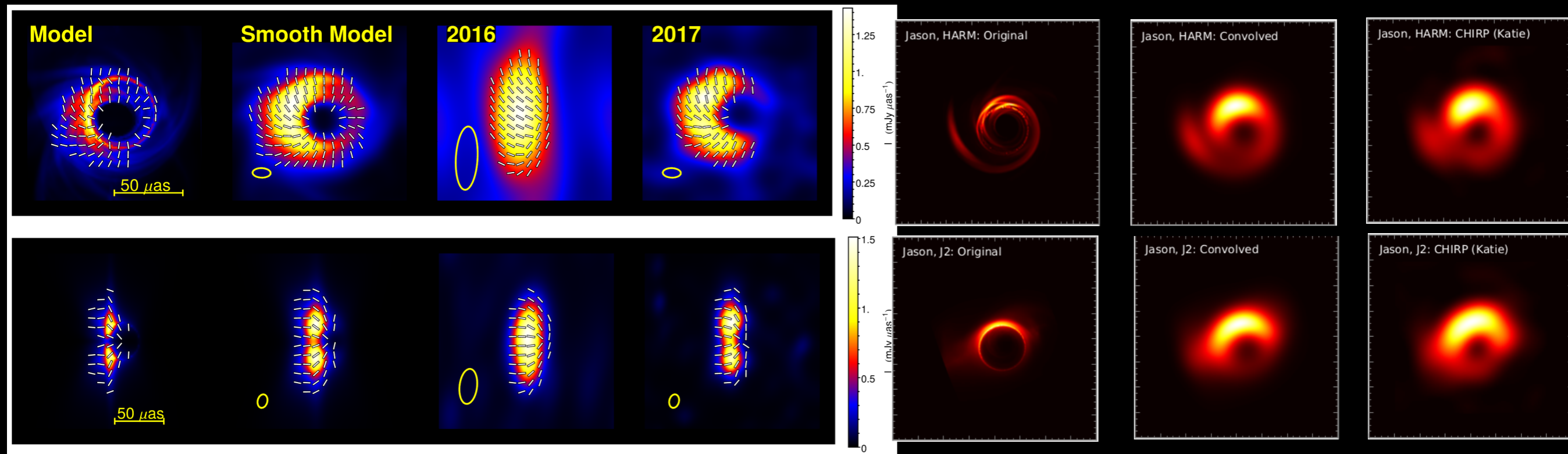
Other imaging techniques from the EHTC

Maximum Entropy Method (MEM)

Chael et al. 2016, Fish et al. 2014,
Lu et al. 2014, 2016

CHIRP (Machine-learning)

Bouman et al. 2016



Challenges for VLBI Imaging

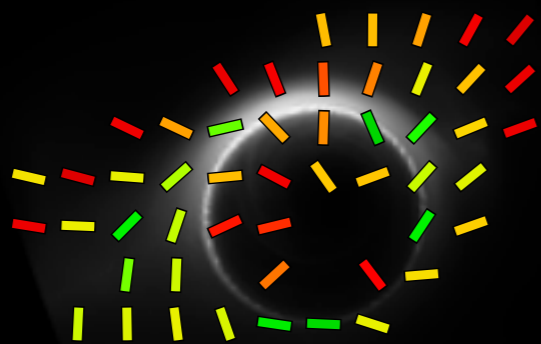


No good phase calibrators!

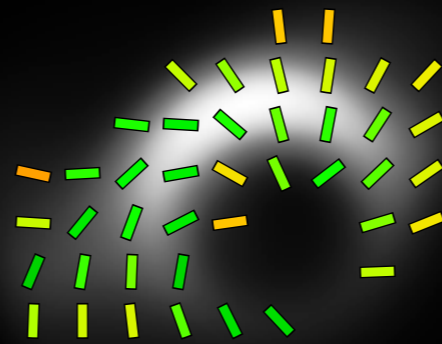
We need to carefully CLEAN so that images are reasonably smooth and sparse, and consistent with closure phases.

Solution: Imaging from Amplitudes + Closure Phases

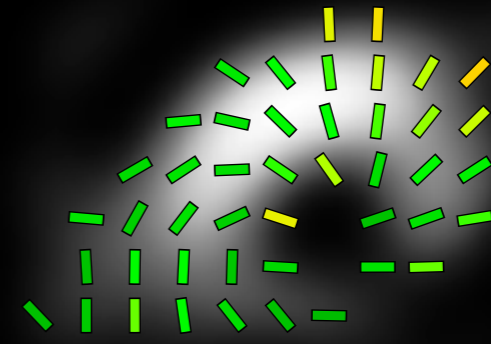
Model



Model (Convolved)



EHT 2017



Sparse Modeling: Akiyama et al. 2017a, Kuramochi et al. 2017

MEM: Lu et al. 2014, 2016, Fish et al. 2016, Chael et al. 2016

CHIRP: Bouman et al. 2016



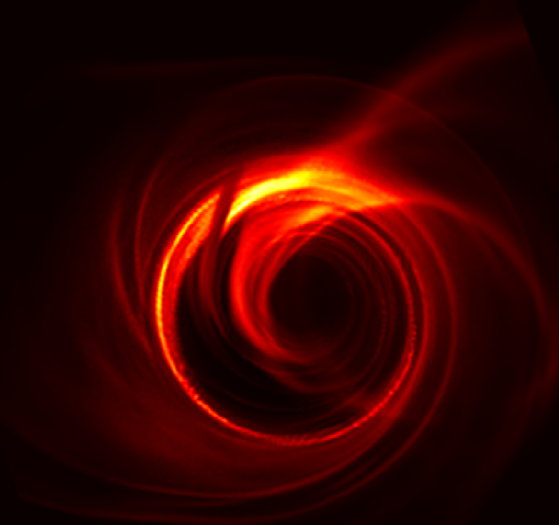
Event Horizon Telescope

Challenges for VLBI Imaging



No good amplitude calibrations!
We need to carefully CLEAN
so that images are consistent with
amplitude gains of $\sim 10\text{-}30\%$, etc. . . .

Solution: Full Closure Imaging (Cl. Amplitudes + Cl. Phase)



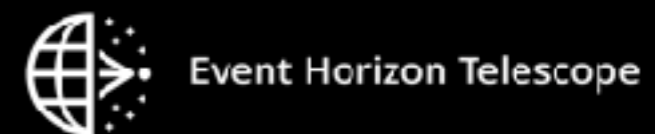
M87 Jet Model
(Moscibrodzka+17)



EHT 2017/2018
Full Closure Imaging

Sparse Modeling: Akiyama et al. in prep.

MEM & CHIRP: Chael et al. in prep.

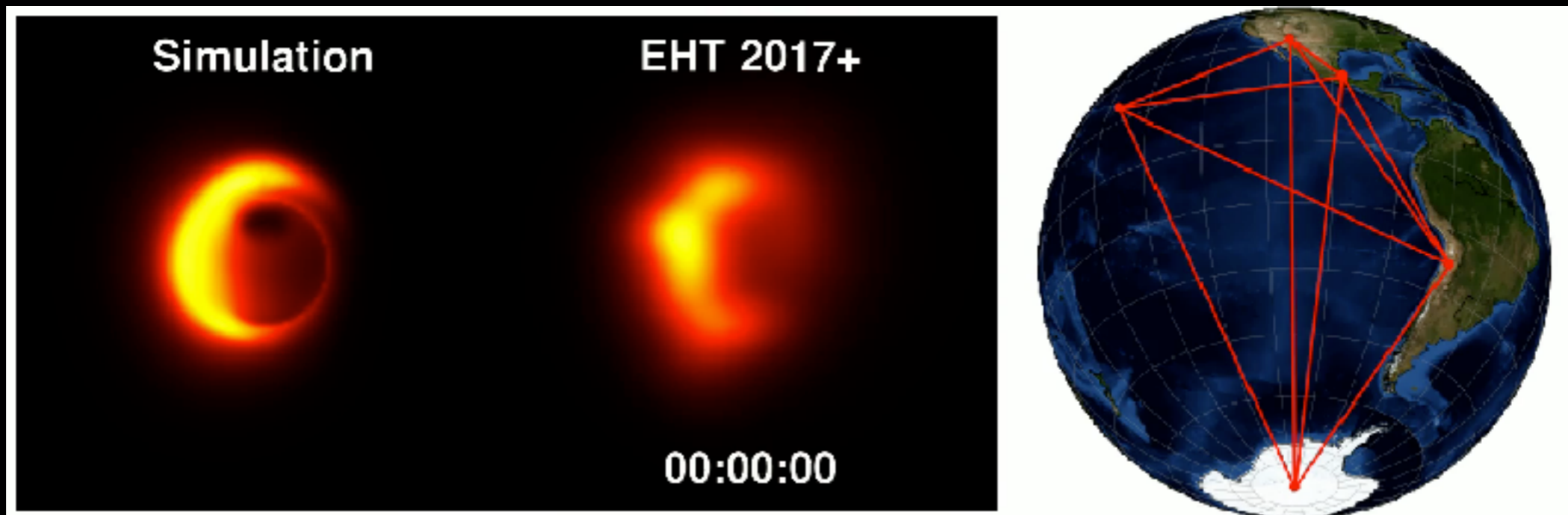


Challenges for VLBI Imaging



Sgr A* (and M87) has a time variability.

Solution: regularize and solve movies.
(extension of sparse and other regularizers in time direction)



(Johnson et al. 2017, ApJ in press;
Bouman et al. 2017, IEEE in press)



Challenges for VLBI Imaging



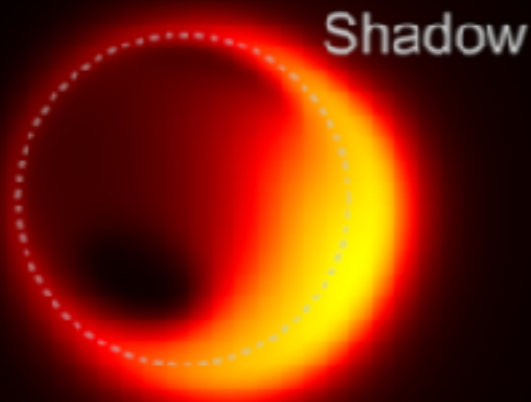
Sgr A* is scattered!

Diffractive scattering: invertible

Refractive scattering: not invertible

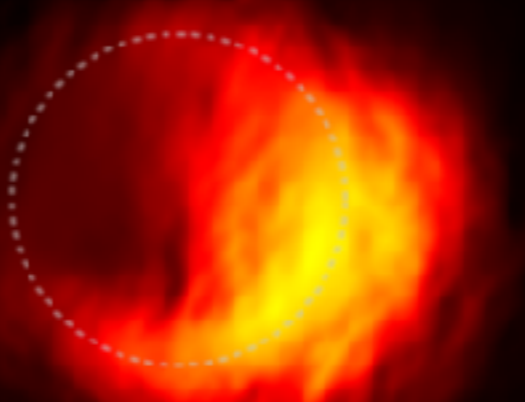
Solution: regularize and solve the phase screen of the refractive scattering as well!

Unscattered

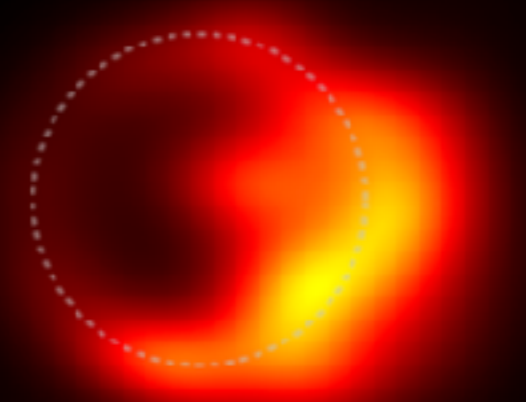


Shadow

Scattered



Stochastic Optics Reconstructions



50 μ as

(Scattering Optics: Johnson 2016, ApJ)

Summary

- Sparse Modeling and other EHT imaging techniques provide a new opportunity to obtain high-quality, high-resolution images (and movies) from various type of interferometric data sets.
- On-going wide application to various sources and other problems
 - Radio Stars, Protoplanetary disks, Jets
 - Faraday Tomography
- Softwares are under development and yet need a certain manpower for applications to real data, but with a huge potential of new sciences and publications !!

If you are willing to try algorithms for your projects, please visit us at MIT Haystack or NAOJ!

We are happy to work with you!



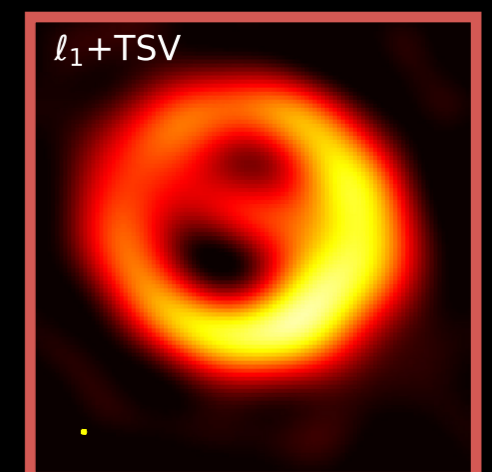
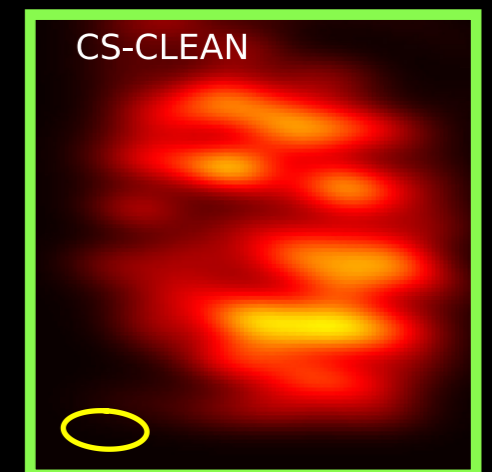
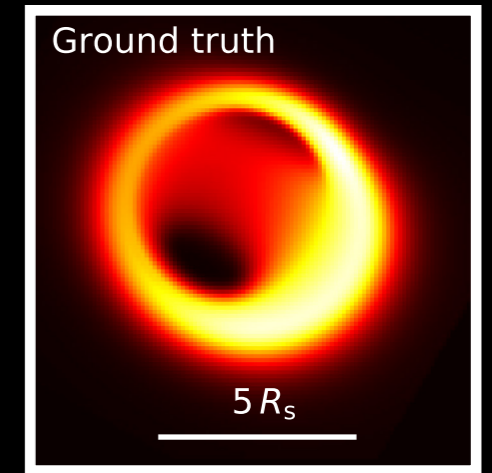
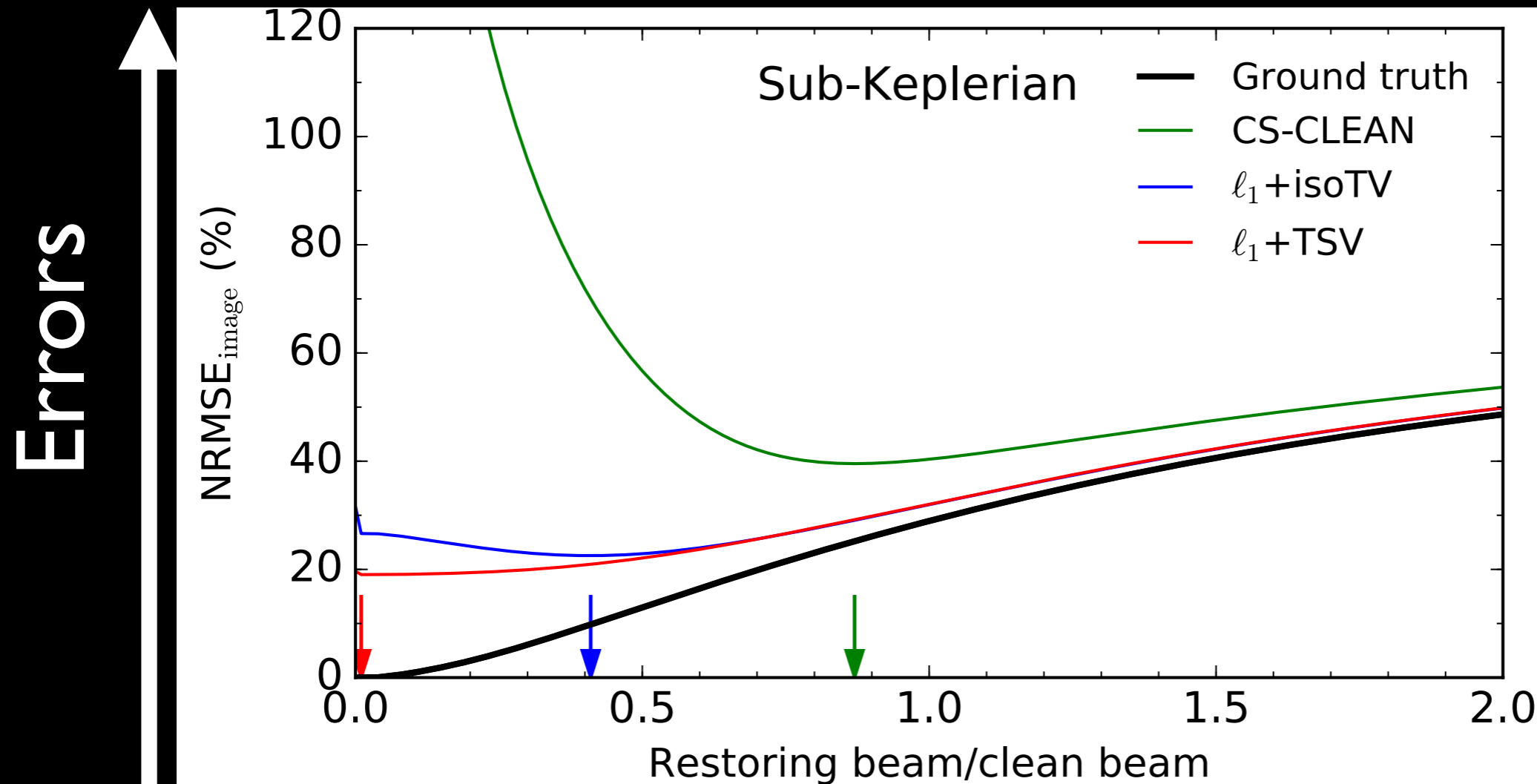
Implementations

- **Sparselab (Akiyama et al.)**
An open source imaging library by EHT-J
- **CASA Sakura Library (Nakazato et al.)**
A FFT-based imaging function is under testing.
- **EHT imaging library (Chael et al.)**
A general imaging & simulation library for the EHT



(Perhaps) no longer need the restoring beam

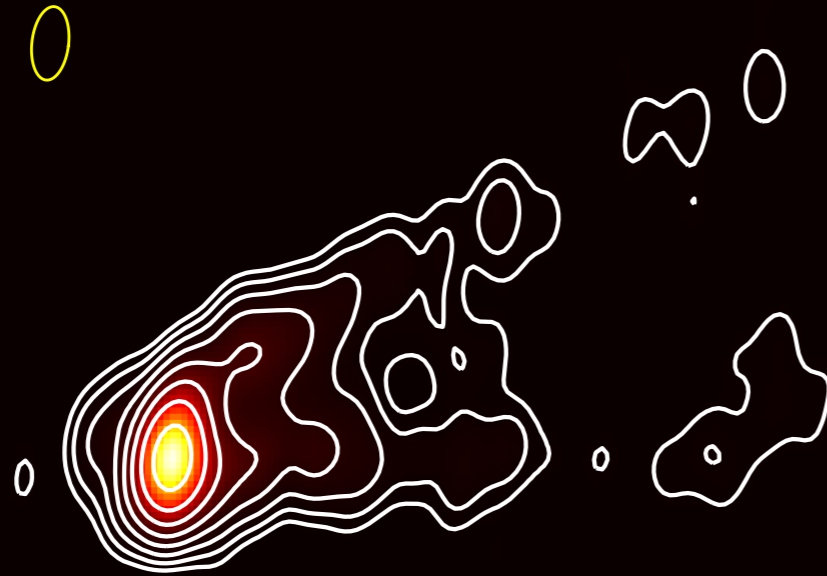
Ground Truth vs Convolved Images



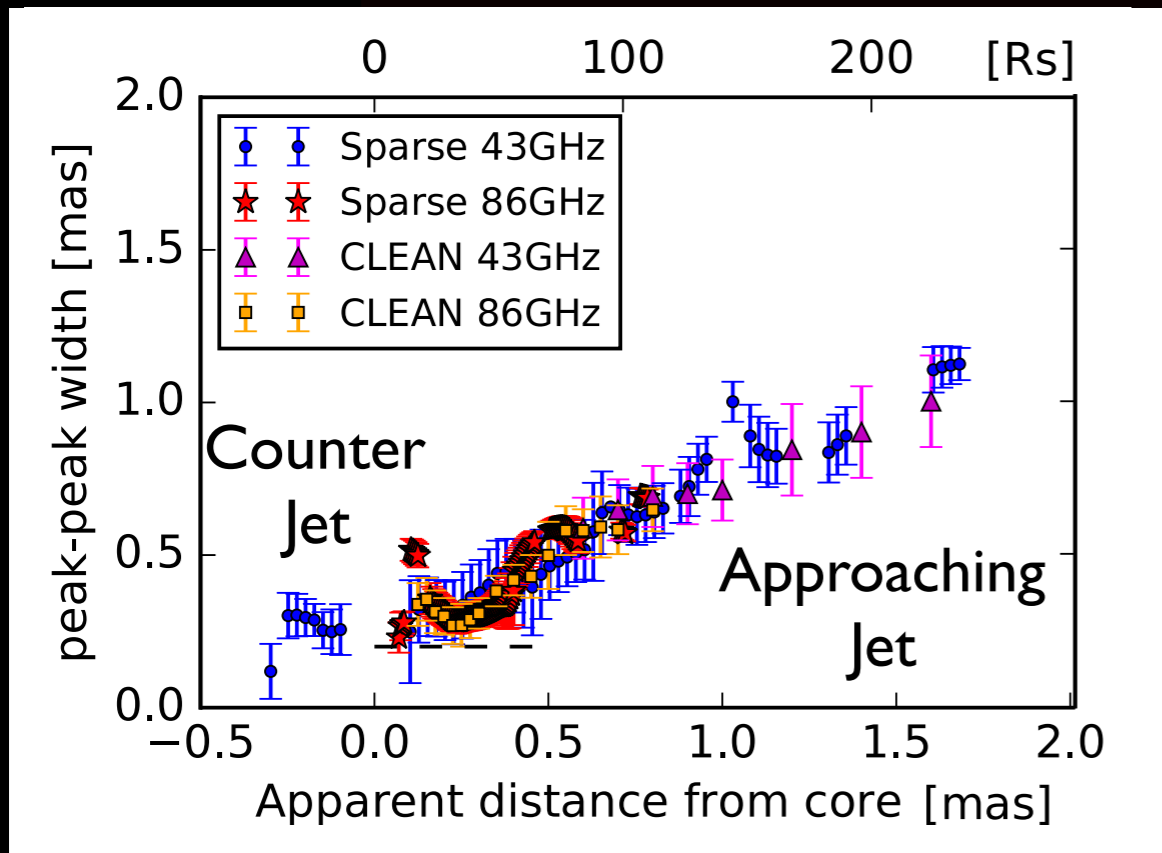
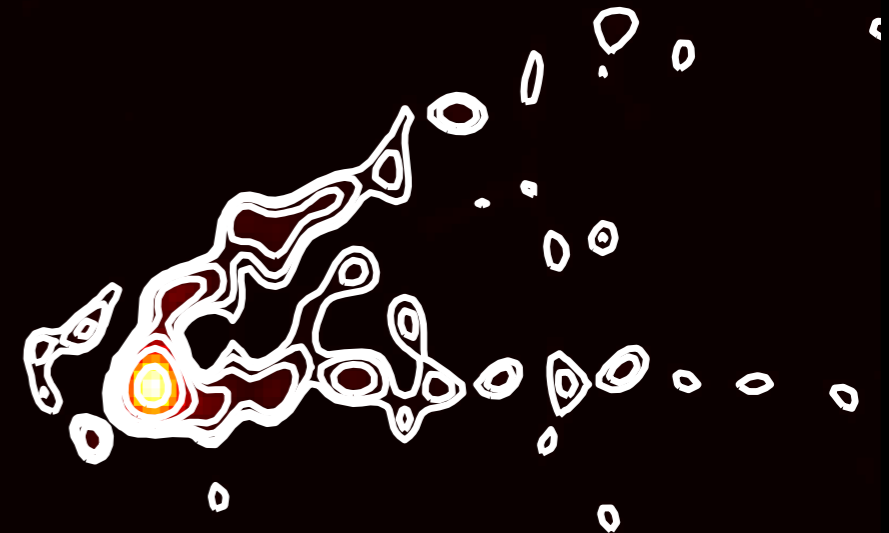
The restoring beam size

Application to Real Data: VLBA M87 Data

CLEAN
(43 GHz)



Sparse
Modeling
(43 GHz)



Clear reproduction of counter jets

Derived collimation profile of the M87 jet is consistent with 86 GHz data

(Tazaki et al., in prep.)