

HARVARD & SMITHSONIAN

Image and non-imaging analysis

Dom Pesce

Center for Astrophysics | Harvard & Smithsonian

20th NRAO Synthesis Imaging Workshop May 17, 2024

What can you do with images?

What can you do with images?

Just about anything!

Classic radio astronomy analyses include various styles of component-wise decomposition of the image into point sources, Gaussians, wavelets, etc.

- many examples exist in the literature
 - source catalog construction from various large-area sky surveys; e.g., <u>Taylor et al. (1996)</u>, <u>Condon et al. (1998)</u>, <u>Mooley et al. (2016)</u>
 - image decomposition into subcomponents; e.g., <u>Miyoshi et al. (1995)</u>, <u>Mertens et al. (2016)</u>

Classic radio astronomy analyses include various styles of component-wise decomposition of the image into point sources, Gaussians, wavelets, etc.

- many examples exist in the literature
 - source catalog construction from various large-area sky surveys; e.g., <u>Taylor et al. (1996)</u>, <u>Condon et al. (1998)</u>, <u>Mooley et al. (2016)</u>
 - image decomposition into subcomponents; e.g., <u>Miyoshi et al. (1995)</u>, <u>Mertens et al. (2016)</u>

Other structures in radio images are often measured/characterized using custom-built feature extraction tools

• e.g., jet position angles and other properties; e.g., <u>Valtonen & Wiik (2012)</u>, <u>Walker et al. (2018)</u>

Classic radio astronomy analyses include various styles of component-wise decomposition of the image into point sources, Gaussians, wavelets, etc.

- many examples exist in the literature
 - source catalog construction from various large-area sky surveys; e.g., <u>Taylor et al. (1996)</u>, <u>Condon et al. (1998)</u>, <u>Mooley et al. (2016)</u>
 - image decomposition into subcomponents; e.g., <u>Miyoshi et al. (1995)</u>, <u>Mertens et al. (2016)</u>

Other structures in radio images are often measured/characterized using custom-built feature extraction tools

• e.g., jet position angles and other properties; e.g., <u>Valtonen & Wiik (2012)</u>, <u>Walker et al. (2018)</u>

The relatively recent explosion of image analysis tools from the machine learning / computer vision communities have permeated into radio astronomical image analyses

 e.g., neural network-based feature extraction; e.g., <u>van der Gucht et al. (2020)</u>, <u>Lin et al. (2020)</u>, <u>Connor et al. (2022)</u>

Matthews et al. (2010) fit two-dimensional Gaussians to thousands of SiO masers observed in Orion Source I

• position measurements over time yield proper motions



Matthews et al. (2010) fit two-dimensional Gaussians to thousands of SiO masers observed in Orion Source I

• position measurements over time yield proper motions

Event Horizon Telescope Collaboration (2019) used image-domain techniques to measure various

properties of the rings of emission seen toward the M87* black hole

• e.g., ring diameter, thickness, orientation



Matthews et al. (2010) fit two-dimensional Gaussians to thousands of SiO masers observed in Orion Source I

• position measurements over time yield proper motions

Event Horizon Telescope Collaboration (2019) used image-domain techniques to measure various properties of the rings of emission seen toward the M87* black hole

e.g., ring diameter, thickness, orientation

ALMA Partnership, Brogan et al. (2015) fit ellipses to the rings in the ALMA image of HL Tau

- measure the disk position angle and inclination
- used to deproject the disk and measure the relative brightnesses of different rings



We'll consider an example dataset from ALMA observations of the water megamaser system in the Circinus AGN

• individual maser "spots" are unresolved



We'll consider an example dataset from ALMA observations of the water megamaser system in the Circinus AGN

individual maser "spots" are unresolved

The location of a maser spot within a single frequency channel can be determined by fitting a Gaussian to the image

- e.g., using the task jmfit in AIPS or the task imfit in CASA
- or your own code!



Pesce et al. (2023)

Declination (J2000)

We'll consider an example dataset from ALMA observations of the water megamaser system in the Circinus AGN

Declination (J2000)

individual maser "spots" are unresolved

The location of a maser spot within a single frequency channel can be determined by fitting a Gaussian to the image

- e.g., using the task jmfit in AIPS or the task imfit in CASA
- or your own code!

In this case, a fit provides:

- (x,y) position
- (major, minor) axis widths
- peak brightness
- position angle



Pesce et al. (2023)

Let's look at the (x,y) locations of just the highest signal-to-noise ratio maser spots



Declination (J2000)

Let's look at the (x,y) locations of just the highest signal-to-noise ratio maser spots

 note that on the plotted scale, the beam is larger than the plot (!)





Let's look at the (x,y) locations of just the highest signal-to-noise ratio maser spots

 note that on the plotted scale, the beam is larger than the plot (!)

Coloring the maser spots by their relative velocity, we can see some evidence for rotation or inflow/outflow in this system

Declination (J2000)



Pesce et al. (2023)

What about uncertainties?

What about uncertainties?

The uncertainties σ_x in position measurements are classically determined using an expression like

$$\sigma_x = k\left(\frac{\Delta_x}{\rho}\right)$$

where Δ_x is a measure of the width, ρ is the signal-to-noise ratio, and k is a proportionality constant whose value depends on the specific function being fit

• for a 2D Gaussian with Δ_x set to the Gaussian FWHM, $k \approx 0.601$ (Condon 1997)

What about uncertainties?

The uncertainties σ_x in position measurements are classically determined using an expression like

$$\sigma_x = k\left(\frac{\Delta_x}{\rho}\right)$$

where Δ_x is a measure of the width, ρ is the signal-to-noise ratio, and k is a proportionality constant whose value depends on the specific function being fit

• for a 2D Gaussian with Δ_x set to the Gaussian FWHM, $k \approx 0.601$ (Condon 1997)



What about uncertainties?

The uncertainties σ_x in position measurements are classically determined using an expression like

$$\sigma_x = k\left(\frac{\Delta_x}{\rho}\right)$$

where Δ_x is a measure of the width, ρ is the signal-to-noise ratio, and k is a proportionality constant whose value depends on the specific function being fit

• for a 2D Gaussian with Δ_x set to the Gaussian FWHM, $k \approx 0.601$ (Condon 1997)

However, this expression (and those like it) assumes:

- that the uncertainty in each pixel value is independent
- that the uncertainty in each pixel value is normally-distributed
- that the number of pixels across the width of the 2D Gaussian is large
- that the signal-to-noise ratio is "high" (i.e., this represents a linearized error estimate)

In practice, most of these conditions are rarely met

The first "analysis" one often wants to do is to simply inspect the data

- characteristics of the image structure can sometimes be seen directly in the visibilities
- can help to determine a good initial model for self-calibration

The first "analysis" one often wants to do is to simply inspect the data

- characteristics of the image structure can sometimes be seen directly in the visibilities
- can help to determine a good initial model for self-calibration

Data may be sparse or even missing (e.g., no phases), or calibration issues may be severe

- in these cases, direct inversion (i.e., deconvolution) may not even be possible
- e.g., high-frequency VLBI (GMVA, KVN, EHT)

The first "analysis" one often wants to do is to simply inspect the data

- characteristics of the image structure can sometimes be seen directly in the visibilities
- can help to determine a good initial model for self-calibration

Data may be sparse or even missing (e.g., no phases), or calibration issues may be severe

- in these cases, direct inversion (i.e., deconvolution) may not even be possible
- e.g., high-frequency VLBI (GMVA, KVN, EHT)

The measurements are natively made in the visibility space

- the measurement uncertainties are well-understood in the visibility space
 - images are not unique! there is no such thing as "the image" corresponding to a dataset
 - for uncertainty quantification, working in the (u,v) space is often simpler
- residual calibration issues live most naturally in the visibility space

The first "analysis" one often wants to do is to simply inspect the data

- characteristics of the image structure can sometimes be seen directly in the visibilities
- can help to determine a good initial model for self-calibration

Data may be sparse or even missing (e.g., no phases), or calibration issues may be severe

- in these cases, direct inversion (i.e., deconvolution) may not even be possible
- e.g., high-frequency VLBI (GMVA, KVN, EHT)

The measurements are natively made in the visibility space

- the measurement uncertainties are well-understood in the visibility space
 - images are not unique! there is no such thing as "the image" corresponding to a dataset
 - for uncertainty quantification, working in the (u,v) space is often simpler
- residual calibration issues live most naturally in the visibility space

Imaging itself is an analysis that uses a non-image data product!

We'll consider an example "a priori unknown" dataset, taken by the MOJAVE team (Lister et al. 2018)

- target source is the quasar NRAO 190
- observations were carried out in December 2019, using the VLBA at 15 GHz

What can we learn about the source just by inspecting the calibrated visibility data?

We'll consider an example "a priori unknown" dataset, taken by the MOJAVE team (Lister et al. 2018)

- target source is the quasar NRAO 190
- observations were carried out in December 2019, using the VLBA at 15 GHz



What can we learn about the source just by inspecting the calibrated visibility data?

Info gathered:



Info gathered:

The visibility amplitudes on the shortest baselines converge to ~1.2 Jy



Info gathered:



Info gathered:

• the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy



Info gathered:

• the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy

The envelope of visibility amplitudes is roughly bounded by Gaussians having σ values of 0.75 and 0.1 mas



Info gathered:

• the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy

The envelope of visibility amplitudes is roughly bounded by Gaussians having σ values of 0.75 and 0.1 mas

Recall:

$$V(u) \approx V(0) + \frac{1}{2}u^2 V''(0)$$

= $V(0) \left[1 - 2\pi^2 u^2 m_2\right]$

For a Gaussian:

$$m_2 = \sigma^2$$


Info gathered:

- the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy
- the source has a FWHM extent that is between ~0.24 mas and ~1.8 mas

The envelope of visibility amplitudes is roughly bounded by Gaussians having σ values of 0.75 and 0.1 mas

Recall:

$$V(u) \approx V(0) + \frac{1}{2}u^2 V''(0)$$

= $V(0) \left[1 - 2\pi^2 u^2 m_2\right]$

For a Gaussian:

$$m_2 = \sigma^2$$



- the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy
- the source has a FWHM extent that is between ~0.24 mas and ~1.8 mas



- the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy
- the source has a FWHM extent that is between ~0.24 mas and ~1.8 mas



- the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy
- the source has a FWHM extent that is between ~0.24 mas and ~1.8 mas
- there's a special orientation at a position angle of ~50 degrees



- the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy
- the source has a FWHM extent that is between ~0.24 mas and ~1.8 mas
- there's a special orientation at a position angle of ~50 degrees
 - that special orientation has a characteristic length scale of $1/150M\lambda \approx 1.4$ mas



Info gathered:

- the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy
- the source has a FWHM extent that is between ~0.24 mas and ~1.8 mas
- there's a special orientation at a position angle of ~50 degrees
 - that special orientation has a characteristic length scale of $1/150M\lambda \approx 1.4$ mas

How does these expectations compare to the actual image reconstruction?



Info gathered:

- the total (i.e., spatially-integrated) flux density in the image should be ~1.2 Jy
- the source has a FWHM extent that is between ~0.24 mas and ~1.8 mas
- there's a special orientation at a position angle of ~50 degrees
 - that special orientation has a characteristic length scale of $1/150M\lambda \approx 1.4$ mas

How does these expectations compare to the actual image reconstruction?

Total flux density = 1.21 Jy

- Second moment principal axes are ~1.35 mas and ~1.5 mas
- beam itself is 0.55 x 1.32 mas

Clear binary structure with a PA of ~50 degrees and a separation of ~1.4 mas



Recall: the basic interferometric data products are "visibilities," which are derived from the complex crosscorrelation between the electric fields incident at pairs of antennas



$$V_{12} = \langle E_1 E_2^* \rangle = A_{12} e^{i\phi_{12}}$$

Recall: the basic interferometric data products are "visibilities," which are derived from the complex crosscorrelation between the electric fields incident at pairs of antennas



$$\hat{V}_{12} = \langle E_1 E_2^* \rangle = A_{12} e^{i \varphi_{12}}$$

 $\hat{V}_{12} = \langle (G_1 E_1) (G_2 E_2)^* \rangle$

$$= G_1 \langle E_1 E_2^* \rangle G_2^*$$
$$= G_1 V_{12} G_2^*$$

Multiplicative complex "gain" effects at each antenna typically constitute the primary systematic corruption of the measured visibilities

 the gains can be difficult to calibrate, particularly at high observing frequencies or for VLBI observations

The classic "closure" quantity is the closure phase (<u>Jennison 1958</u>), which is the argument of the product of visibilities around a triangle of baselines

$$\hat{V}_{12}\hat{V}_{23}\hat{V}_{31} = (G_1V_{12}G_2^*)(G_2V_{23}G_3^*)(G_3V_{31}G_1^*)$$



The classic "closure" quantity is the closure phase (<u>Jennison 1958</u>), which is the argument of the product of visibilities around a triangle of baselines

$$\hat{V}_{12}\hat{V}_{23}\hat{V}_{31} = (G_1V_{12}G_2^*)(G_2V_{23}G_3^*)(G_3V_{31}G_1^*)$$

 $= (G_1 G_1^*) (G_2 G_2^*) (G_3 G_3^*) V_{12} V_{23} V_{31}$



The classic "closure" quantity is the closure phase (<u>Jennison 1958</u>), which is the argument of the product of visibilities around a triangle of baselines

$$\hat{V}_{12}\hat{V}_{23}\hat{V}_{31} = (G_1V_{12}G_2^*)(G_2V_{23}G_3^*)(G_3V_{31}G_1^*)$$

 $= (G_1 G_1^*) (G_2 G_2^*) (G_3 G_3^*) V_{12} V_{23} V_{31}$



$$\arg\left(\hat{V}_{12}\hat{V}_{23}\hat{V}_{31}\right) = \arg\left(V_{12}V_{23}V_{31}\right)$$
$$\hat{\phi}_{12} + \hat{\phi}_{23} + \hat{\phi}_{31} = \phi_{12} + \phi_{23} + \phi_{31}$$

A key property of the closure phase is that it is invariant to station-based phase corruptions, making it a "robust" observable

The classic "closure" quantity is the closure phase (<u>Jennison 1958</u>), which is the argument of the product of visibilities around a triangle of baselines



Readhead, Napier,

<u>& Bignell (1980)</u>

The classic "closure" quantity is the closure phase (<u>Jennison 1958</u>), which is the argument of the product of visibilities around a triangle of baselines

Closure phases are difficult to interpret directly, but encode a measure of the "asymmetry" of a source

- any point-symmetric source will have zerovalued closure phases
- nonzero values indicate a departure from point symmetry



Readhead, Napier,

& Bignell (1980)

The classic "closure" quantity is the closure phase (<u>Jennison 1958</u>), which is the argument of the product of visibilities around a triangle of baselines

Closure phases are difficult to interpret directly, but encode a measure of the "asymmetry" of a source

- any point-symmetric source will have zerovalued closure phases
- nonzero values indicate a departure from point symmetry

However, closure phases are also insensitive to an overall phase gradient

• equivalently, closure phases are insensitive to the absolute position of the source because $m{u}_{12} + m{u}_{23} + m{u}_{31} = 0$



Readhead, Napier, & Bignell (1980)

The classic "closure" quantity is the closure phase (<u>Jennison 1958</u>), which is the argument of the product of visibilities around a triangle of baselines



In addition to the closure phase, an amplitude quantity – called a "closure amplitude" – can be formed from a closed loop of four stations (Twiss, Carter, & Little 1960)

$$\frac{\hat{V}_{12}\hat{V}_{34}}{\hat{V}_{23}\hat{V}_{41}} = \frac{(G_1V_{12}G_2^*)(G_3V_{34}G_4^*)}{(G_2V_{23}G_3^*)(G_4V_{41}G_1^*)}$$



In addition to the closure phase, an amplitude quantity – called a "closure amplitude" – can be formed from a closed loop of four stations (<u>Twiss, Carter, & Little 1960</u>)

$$\begin{aligned} \frac{\hat{V}_{12}\hat{V}_{34}}{\hat{V}_{23}\hat{V}_{41}} &= \frac{(G_1V_{12}G_2^*)(G_3V_{34}G_4^*)}{(G_2V_{23}G_3^*)(G_4V_{41}G_1^*)} \\ &= \left(\frac{G_1}{G_1^*}\right)\left(\frac{G_2^*}{G_2}\right)\left(\frac{G_3}{G_3^*}\right)\left(\frac{G_4^*}{G_4}\right) \\ \hat{V}_{34} &= G_3V_{34}G_4^* \\ \hat{V}_{12} &= G_1V_{12}G_2^* \qquad \text{antenna 3} \\ \hat{V}_{23} &= G_2V_{23}G_3^* \end{aligned}$$

 $\frac{V_{12}V_{34}}{V_{23}V_{41}}$

In addition to the closure phase, an amplitude quantity – called a "closure amplitude" – can be formed from a closed loop of four stations (Twiss, Carter, & Little 1960)

$$\begin{aligned} \frac{\hat{V}_{12}\hat{V}_{34}}{\hat{V}_{23}\hat{V}_{41}} &= \frac{(G_1V_{12}G_2^*)(G_3V_{34}G_4^*)}{(G_2V_{23}G_3^*)(G_4V_{41}G_1^*)} \\ &= \left(\frac{G_1}{G_1^*}\right)\left(\frac{G_2^*}{G_2}\right)\left(\frac{G_3}{G_3^*}\right)\left(\frac{G_4^*}{G_4}\right)\frac{V_4}{V_4} \\ \hat{V}_{12} &= G_1V_{12}G_2^* \\ \hat{V}_{12} &= G_1V_{12}G_2^* \\ \hat{V}_{23} &= G_2V_{23}G_3^* \end{aligned}$$

 $V_{12}V_{34}$

antenna 2

antenna 1

Between them, the closure phases and amplitudes represent a "complete" set of observables

• i.e., all station gain-independent information in the complex visibilities is retained in the closure phases and amplitudes (<u>Blackburn et al. 2019</u>)

Between them, the closure phases and amplitudes represent a "complete" set of observables

• i.e., all station gain-independent information in the complex visibilities is retained in the closure phases and amplitudes (<u>Blackburn et al. 2019</u>)

For full-Stokes observations, additional station-based corruptions in the form of polarization leakage become important

- more heavily composite quantities such as "closure traces" (<u>Broderick & Pesce 2020</u>) and "closure invariants" (<u>Samuel</u>, <u>Nityananda, & Thyagarajan 2022</u>) can be constructed that are insensitive to *all* station-based corruptions, including gains and leakage (both phase and amplitude)
- can be used to determine the presence of polarized flux in the source



"Forward" modeling techniques – as contrasted with "inverse" modeling techniques – permit fitting a parameterized model to any desired data product(s)

- inverse modeling directly manipulates the data to produce an estimate of the desired quantity/quantities (e.g., CLEAN)
- forward modeling instead uses a "guess and check" approach

"Forward" modeling techniques – as contrasted with "inverse" modeling techniques – permit fitting a parameterized model to any desired data product(s)

- inverse modeling directly manipulates the data to produce an estimate of the desired quantity/quantities (e.g., CLEAN)
- forward modeling instead uses a "guess and check" approach



"Forward" modeling techniques – as contrasted with "inverse" modeling techniques – permit fitting a parameterized model to any desired data product(s)

- inverse modeling directly manipulates the data to produce an estimate of the desired quantity/quantities (e.g., CLEAN)
- forward modeling instead uses a "guess and check" approach



"Forward" modeling techniques – as contrasted with "inverse" modeling techniques – permit fitting a parameterized model to any desired data product(s)

- inverse modeling directly manipulates the data to produce an estimate of the desired quantity/quantities (e.g., CLEAN)
- forward modeling instead uses a "guess and check" approach

The increased power + flexibility of forward modeling typically comes at the cost of increased computational expense

• for simple models and modest data volumes, a forward modeling strategy can often be viable

"Forward" modeling techniques – as contrasted with "inverse" modeling techniques – permit fitting a parameterized model to any desired data product(s)

- inverse modeling directly manipulates the data to produce an estimate of the desired quantity/quantities (e.g., CLEAN)
- forward modeling instead uses a "guess and check" approach

The increased power + flexibility of forward modeling typically comes at the cost of increased computational expense

• for simple models and modest data volumes, a forward modeling strategy can often be viable

Forward modeling techniques typically seek to either optimize some sort of objective function (e.g., minimize a χ^2 , maximize a likelihood) or else to explore the posterior distribution over some set of model parameters

- data uncertainties naturally map to uncertainties on derived parameters
- complex visibilities typically have independent Gaussian uncertainties (!)
 - see, e.g., <u>Thompson, Moran, & Swenson</u> and <u>Blackburn et al. (2019)</u> for other data products

Simple analytic models: point source

The simplest image structure is a point source:

- flux density S₀
- location (x_0, y_0)





Simple analytic models: point source

The simplest image structure is a point source:

- flux density S₀
- location (x_0, y_0)





Simple analytic models: point source

The simplest image structure is a point source:

- flux density S₀
- location (x_0, y_0)

$$V(u,v) = S_0 e^{-2\pi i (ux_0 + vy_0)}$$



Gaussians are very popular components to use in interferometric data analysis:

- flux density S₀
- location (x_0, y_0)

width σ

- $V(u,v) = S_0 e^{-2\pi i (ux_0 + vy_0)} e^{-2\pi^2 \sigma^2 (u^2 + v^2)}$
- Amplitude (Jy) 4 -.0 2 -0.5 ADec (mas) 0 -0.0 100 · Phase (deg.) -2 -0 -100-4 -100 200 300 -2400 2 500 -40 4 0 ΔRA (mas) u (M λ)

Gaussians are very popular components to use in interferometric data analysis:

- flux density S₀
- location (x_0, y_0)

width σ

- $V(u,v) = S_0 e^{-2\pi i (ux_0 + vy_0)} e^{-2\pi^2 \sigma^2 (u^2 + v^2)}$
- Amplitude (Jy) 4 -1.02 -0.5 ADec (mas) 0 -0.0 Phase (deg.) 100 -20 -100-4 -100 200 300 400 -22 500 0 4 0 -4ΔRA (mas) u (M λ)

Gaussians are very popular components to use in interferometric data analysis:

- flux density S₀
- location (x_0, y_0)
- width σ

$$V(u,v) = S_0 e^{-2\pi i (ux_0 + vy_0)} e^{-2\pi^2 \sigma^2 (u^2 + v^2)}$$



Gaussians are very popular components to use in interferometric data analysis:

- flux density S₀
- location (x_0, y_0)
- width σ

$$V(u,v) = S_0 e^{-2\pi i (ux_0 + vy_0)} e^{-2\pi^2 \sigma^2 (u^2 + v^2)}$$



Simple analytic models

There are other analytic models that get used with some frequency as well:



Simple analytic models

There are other analytic models that get used with some frequency as well:


Some other useful Fourier transform properties

There are a number of useful mappings between manipulations of the image and visibility domains, of which some of the simplest are:

<u>linearity</u>: $aI(x,y) + b \longrightarrow aV(u,v) + b$

Some other useful Fourier transform properties

There are a number of useful mappings between manipulations of the image and visibility domains, of which some of the simplest are:

linearity:
$$aI(x, y) + b \longrightarrow aV(u, v) + b$$

scaling:
$$I(ax, by) \longrightarrow \frac{1}{ab} V\left(\frac{u}{a}, \frac{v}{b}\right)$$

Some other useful Fourier transform properties

There are a number of useful mappings between manipulations of the image and visibility domains, of which some of the simplest are:

linearity:
$$aI(x,y) + b \longrightarrow aV(u,v) + b$$

$$\underline{\text{scaling}}: \quad I(ax, by) \quad \longrightarrow \quad \frac{1}{ab} V\left(\frac{u}{a}, \frac{v}{b}\right)$$

<u>convolution theorem</u>: $I_1(x,y) \times I_2(x,y) \longrightarrow V_1(u,v) * V_2(u,v)$

Details on these and other properties (e.g., translations, derivatives, moments) can be found in <u>Thompson</u>, <u>Moran, & Swenson</u> (Chapter 2) and elsewhere

Examples of visibility-domain model fitting

The precessing jet in the microquasar V404 Cygni evolves too quickly for Earth rotation aperture synthesis to be appropriate

• <u>Miller-Jones et al. (2019)</u> instead fit short segments of data using point source decomposition



Video credit: Alex Tetarenko

Examples of visibility-domain model fitting

The precessing jet in the microquasar V404 Cygni evolves too quickly for Earth rotation aperture synthesis to be appropriate

• <u>Miller-Jones et al. (2019)</u> instead fit short segments of data using point source decomposition

The appearance of Sgr A* is heavily blurred-out at radio frequencies by interstellar scattering

 <u>Bower et al. (2014)</u> and <u>Johnson et al. (2021)</u> fit a Gaussian to Sgr A* using closure quantities to measure the scattering kernel



Examples of visibility-domain model fitting

The precessing jet in the microquasar V404 Cygni evolves too quickly for Earth rotation aperture synthesis to be appropriate

• <u>Miller-Jones et al. (2019)</u> instead fit short segments of data using point source decomposition

The appearance of Sgr A* is heavily blurred-out at radio frequencies by interstellar scattering

 <u>Bower et al. (2014)</u> and <u>Johnson et al. (2021)</u> fit a Gaussian to Sgr A* using closure quantities to measure the scattering kernel

Analysis of the blazar 3C 279 as observed by the EHT revealed a rapid evolution in time over just a few days 10^{-80}

• <u>Kim et al. (2020)</u> fit time-variable Gaussian model components to measure brightness changes and speeds of the many different source components



Let's return to the example dataset from before, with the ALMA observations of water masers in the Circinus AGN

- calibrated visibility data in a single frequency channel look point-like
- individual data point uncertainties are large and not necessarily well-known



Let's return to the example dataset from before, with the ALMA observations of water masers in the Circinus AGN

- calibrated visibility data in a single frequency channel look point-like
- individual data point uncertainties are large and not necessarily well-known

We can fit a point-source model directly to the visibility data, with free parameters for:

- the total flux density, S
- the (*x*,*y*) location
- the visibility uncertainty, σ



Let's return to the example dataset from before, with the ALMA observations of water masers in the Circinus AGN

- calibrated visibility data in a single frequency channel look point-like
- individual data point uncertainties are large and not necessarily well-known

We can fit a point-source model directly to the visibility data, with free parameters for:

- the total flux density, S
- the (*x*,*y*) location
- the visibility uncertainty, σ

Result:

- *S* = 1.06 Jy
- *x* = 79 mas
- *y* = 213 mas
- σ = 0.71 Jy



Pesce et al. (2023)

(fit using dynesty; Speagle 2020)

Let's return to the example dataset from before, with the ALMA observations of water masers in the Circinus AGN

- calibrated visibility data in a single frequency channel look point-like
- individual data point uncertainties are large and not necessarily well-known

We can fit a point-source model directly to the visibility data, with free parameters for:

- the total flux density, S
- the (*x*,*y*) location
- the visibility uncertainty, σ

Result:

- *S* = 1.06 ± 0.03 Jy
- *x* = 79 ± 7 mas
- *y* = 213 ± 8 mas
- $\sigma = 0.71 \pm 0.01 \text{ Jy}$



Pesce et al. (2023)

(fit using dynesty; Speagle 2020)

Applying the same point-source model to each frequency channel, we can re-generate the map from earlier



Declination (J2000)

Applying the same point-source model to each frequency channel, we can re-generate the map from earlier

Tracking the same strong maser spots as before, we can see that they have become more concentrated

Declination (J2000)



Applying the same point-source model to each frequency channel, we can re-generate the map from earlier

Tracking the same strong maser spots as before, we can see that they have become more concentrated

We now have access to reliable (2D) uncertainty information for each spot, and we can see that indeed the most tightlyconstrained positions occur where the spots are most densely concentrated Declination (J2000)

- i.e., the map exhibits self-consistency
- furthermore, the shapes of the error ellipses closely mirror the beam shape



For this system, we happen to know how it behaves from prior VLBI observations

good agreement despite ~3 orders of magnitude difference in beam size (!)



 $-65^{\circ}20'20.8''$

Summary

Interferometric image reconstructions can be analyzed in any way that other images can be

- common procedures include multi-source or multi-component decomposition, though many other feature extraction analyses have also been employed
- uncertainty estimates on derived quantities are difficult to determine

However, interferometric data do not natively take the form of images, and *non-imaging analyses* are typically both the first (e.g., data inspection) and often the most precise (e.g., uncertainty quantification) means of extracting science

One has many options available during data inspection to understand basic properties of a dataset

- closure quantities (both phases and amplitudes) are immune to various station-based data corruptions and encode information about a source's (a)symmetry
- closure traces and invariants are further immune to polarimetric leakage and encode information about a source's polarization state

Forward modeling is a powerful quantitative analysis tool

- any data products can be forward modeled, not just visibilities
- measurement uncertainties on visibilities are typically independent and close to Gaussian, enabling accurate uncertainty estimates for derived / fit quantities