CASA VLBI



LECTURE 6: TYPICAL DATA ISSUES



I. MARTI-VIDAL (University of Valencia, SPAIN)





Typical Data Issues with VLBI

Identifying and Correcting Gain-related and Noise-related Problems

Ivan Martí-Vidal

Observatori Astronòmic & Dpt. Astronomia i Astrofísica Universitat de València (GIDEGENT Research Program, GVA)

CASA-VLBI Workshop 2020 - JIVE (Netherlands)

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Typical Data Issues



• Bad Gains.

- Effects on visibilities and images.
- ▶ The "effective" PSF from bad gains. Dynamic-range limitations.
- Amplitude vs. phase gain issues.
- Locating problematic visibilities during deconvolution.

Bad Data.

- Sensitivity limitation.
- Noise-dominated visibility distributions.
- ► A "crazy" self-calibration.

Bad Sources.

Bandwidth effects.

BAD GAINS

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Back to the Origins



The *true* image brightness distribution, $\mathcal{I}^{\text{true}}(x, y)$ is related to the visibility function, $\mathcal{V}(u, v)$ via the equation: $\mathcal{I}^{\text{true}}(x, y) = \int_{(u,v)} \mathcal{V}(u, v) e^{2\pi j(ux+vy)} du dv$

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powever, we only measure
$$\mathcal{V}(u, v)$$
 in a finite set of (u, v) points, a.k.a. the uv-coverag (u, v) . We thus reconstruct a dirty image. $\mathcal{I}^{\text{dirty}}(x, v)$:

$$\mathcal{I}^{\text{dirty}}(x,y) = \int_{(u,v)} \mathcal{V}(u,v) \,\mathcal{C}(u,v) \,e^{2\pi j(ux+vy)} du \,dv$$

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$$\mathcal{I}^{\text{dirty}}(\mathbf{x},\mathbf{y}) = \int_{(u,v)} \mathcal{V}(u,v) \,\mathcal{C}(u,v) \,e^{2\pi j(ux+vy)} du \,dv$$

Using the well-known Convolution Theorem: $\mathcal{I}^{\text{dirty}}(x,y) = \mathcal{I}^{\text{true}}(x,y) * B(x,y)$

where
$$B(x, y) = \int_{(u,v)} \mathcal{C}(u, v) e^{2\pi j(ux+vy)} du dv$$

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The Origins Revisited



We actually measure a somewhat *corrupted* version of $\mathcal{V}^{obs}(u, v)$:

$$\mathcal{V}^{\mathrm{obs}}(u,v) = \mathcal{V}(u,v) \times (1 + \mathcal{G}(u,v))$$

Hence, the recovered image is:

$$\mathcal{I}^{\mathrm{obs}}(x,y) = \int_{(u,v)} \mathcal{V}(u,v) \mathcal{C}(u,v) (1 + \mathcal{G}(u,v)) e^{2\pi j (ux+vy)} du dv$$

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From the Convolution Theorem, we get: $\mathcal{I}^{obs}(x,y) = \mathcal{I}^{true}(x,y) * (B(x,y) + G(x,y))$

where
$$G(x, y) = \int_{(u,v)} \mathcal{C}(u, v) \mathcal{G}(u, v) e^{2\pi j(ux+vy)} du dv$$

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The Gain Problem



The images $\mathcal{I}^{obs}(x, y)$ and $\mathcal{I}^{dirty}(x, y)$ are convolved with different PSFs. However, we use the PSF of $\mathcal{I}^{dirty}(x, y)$ to deconvolve $\mathcal{I}^{obs}(x, y)$. In other words, we use the wrong point-spread function for the deconvolution!:

 $\mathcal{I}^{\mathrm{obs}}(x,y) = \mathcal{I}^{\mathrm{true}}(x,y) * (B(x,y) + G(x,y)) \quad ; \quad \mathcal{I}^{\mathrm{dirty}}(x,y) = \mathcal{I}^{\mathrm{true}}(x,y) * B(x,y)$

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Wrong antenna gains have a convolution-like effect in the image plane. The true convolving PSF and the one computed from the uv-coverage are different.

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Wrong antenna gains have a convolution-like effect in the image plane. The true convolving PSF and the one computed from the uv-coverage are different.

This introduces dynamic-range limitations in the image (i.e., the noise is proportional to the image peak, hence limiting the achievable contrast).

Gains and Dynamic Range





Point source with weak companion (CLEANing perfectly-calibrated data).

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Gains and Dynamic Range





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Gains and Dynamic Range





Point source with weak companion (CLEANing data with calibration issues).

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How do $\mathcal{G}(u, v)$ and $\mathcal{G}(x, y)$ behave?

• Amplitude gain: $\mathcal{G}(u, v)$ is real-valued and even. Hence, $\mathcal{G}(x, y)$ is even.

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How do $\mathcal{G}(u, v)$ and $\mathcal{G}(x, y)$ behave?

• Amplitude gain: $\mathcal{G}(u, v)$ is real-valued and even. Hence, $\mathcal{G}(x, v)$ is even.

EXAMPLE: 6h with WSRT at 45° Declination (done with APSYNSIM):

Perfect calibration

4.39e-02 ly/beam at point $\Delta \alpha = 0.00 / \Delta \delta = 0.00$ Peak: 2.00 ly/beam : rms: 0.11 ly/beam

50% Amplitude in one antenna



CLEAN residuals



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How do $\mathcal{G}(u, v)$ and G(x, y) behave? • Small Phase gain: $\mathcal{G}(u, v)$ is imaginary and odd. Hence, G(x, y) is odd.

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EXAMPLE: 6h with WSRT at 45° Declination (done with APSYNSIM):



20° Phase in one antenna



CLEAN residuals





Which EVN baseline and gain dominates these residuals?







Which EVN baseline and gain dominates these residuals?



• B. Ro - Tr. Amplitude gain.

• D. Hh - Ur. Phase gain.

Reality is usually worse



How can we identify the bad gains in the general case?



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Reality is usually worse





How can we identify the bad gains in the general case?

The residual image encodes the spatial frequencies of G(x, y)!

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The "checkres" task (Nordic ARC Node)

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The plotms task





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The plotms task





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So, what do we do?



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SELF-CALIBRATION! Iterative hybrid imaging!

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SELF-CALIBRATION! Iterative hybrid imaging!

But remember: with great power comes great responsibility (see next slides)

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BAD DATA

Bad data is worse than no data at all. Alan Marsher

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Noise in the visibilities



- Assuming a correct calibration, the real and imaginary parts of the visibilities have Gaussian and independent thermal noise.
- Hence, the amplitudes and phase do **NOT** have neither Gaussian nor independent noises.







What is the flux density of the point source in these observations?



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What is the flux density of the point source in these observations?



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Beware of noisy selfcal!



Self-calibrating on noisy data can create spurious sources with a flux density, F_{sp} , similar to the rms of the visibilities, ρ ! (e.g., Martí-Vidal & Marcaide 2008).

$$F_{sp} \sim 0.7
ho \sqrt{rac{t_{
m int}}{t_{
m sol}}} N_{
m ant}^{-0.4}$$



A crazy self-calibration



Pure thermal noise observed with the EVN (30° declination, 6h with optimum elevations).



A crazy self-calibration



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Only phase self-calibration with an a-priori model. Pretty "harmless", ain't it?



A crazy self-calibration



Only phase self-calibration with an a-priori model. Pretty "harmless", ain't it?





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BAD SOURCES

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Increasing the SNR by averaging



- We can do averaging either in time or frequency (or both).
- Averaging in uv-space is a *convolution-like* operation (substitutes tracks and lines by points).
- From the convolution theorem, the effects in the image plane are "product-like".
 - Time Smearing and Bandwidth Smearing (baseline-dependent smearing of source components far from the phase center).

$$\text{FoV}(\text{arcsec}) = \max\left[11\left(\frac{t_{\text{int}}}{1\,\text{s}}\right)^{-1} , 4.8\left(\frac{\Delta\nu}{1\,\text{MHz}}\right)^{-1}\right] \times \left(\frac{B_{\text{max}}}{10^4\,\text{km}}\right)^{-1}$$

Source frequency dependence



• For large bandwidths, the source's spectral distribution can limit the dynamic range.



Double source with different spectral indices ($\alpha = 0.0$ for the core; $\alpha = -1.0$ for the extension). In red, CLEAN in normal mode; In white, CLEAN in multi-frequency-synthesis (mfs) mode.

SUMMARY



- Images are limited by uv-coverage and antenna gains. Both have convolution-like effects.
- If there is an incorrect calibration, it is possible to identify the bad gains from the residuals:
 - Find out the bad spatial frequencies in the residual image and identify the bad points (e.g., the "checkres" task).
 - Check the residual visibilities and look for outliers: phases in data/model or amplitudes in data-model (the "plotms" task).
- Once the bad data are identified, we can correct them with self-calibration. BUT, special care has to be taken with noisy data.
- Even if the data are perfectly calibrated, we can still introduce artifacts, e.g.:
 - Smearing effects from visibility averaging.
 - Dynamic-range limitation by source spectral distribution in wideband observations.

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