Imaging at low frequencies

André Offringa (ASTRON) Bologna, Italy, 2017-06-20



(b) Residual image (σ =8.6 units/PSF)

Automatic scale-dependent masking applied on the UGC12591 test-set.



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Challenges in low-frequency imaging

- Large FOV
 - Large w-values
 - Harder to deconvolve
- Large fractional bandwidth
 - Requires multi-frequency deconvolution
- Large data volumes
- Robustness to calibration errors
- Connection to direction-dependent cal.

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An optimized algorithm for multi-scale wideband deconvolution of radio astronomical images

A. R. Offringa^{1*}, O. Smirnov^{2,3}

¹Netherlands Institute for Radio Astronomy (ASTRON), PO Box 2, 7990 AA Dwingeloo, The Netherlands ²Department of Physics and Electronics, Rhodes University, PO Box 94, Grahamstown, 6140, South Africa ³SKA South Africa, 3rd Floor, The Park, Park Road, Pinelands, 7405, South Africa

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Accepted yesterday!

ABSTRACT

We describe a new multi-scale deconvolution algorithm that can also be used in multifrequency mode. The algorithm only affects the minor clean loop. In single-frequency mode, the minor loop of our improved multi-scale algorithm is over an order of magnitude faster than the CASA multi-scale algorithm, and produces results of similar quality. For multi-frequency deconvolution, a technique named joined-channel cleaning is used. In this mode, the minor loop of our algorithm is 2-3 orders of magnitude faster than CASA MSMFS. We extend the multi-scale mode with automated scale-dependent masking, which allows structures to be cleaned below the noise. We describe a new scale-bias function for use in multi-scale cleaning. We test a second deconvolution method that is a variant of the MORESANE deconvolution technique, and uses a convex optimisation technique with isotropic undecimated wavelets as dictionary. On simple, well calibrated data the convex optimisation algorithm produces visually more representative models. On complex or imperfect data, the convex optimisation algorithm has stability issues.

WSClean: w-stacking



A few examples of WSClean results...



"The LWA1 Low Frequency Sky Survey", Jayce Dowell et al. (2017)



Gravitational Lense (VLBI data by J. P. McKean and C. Spingola)



GLEAM, N. Hurley-Walker et al. (2017)



MWA EoR0, Offringa et al. (2016). Deepest MWA image.

 Common approach in MF deconvolution is imaging / predicting "frequency derivative" images ("nterms>1", the Sault & Wieringa (1994) method).

That results in:





Instead, WSClean splits the bandwidth and creates separate images for each part:

(Similar strategy is used by B. Cotton's OBIT)

- Common approach in MF deconvolution is imaging /
- Of course, these contain the same information
 - (they can be converted from one to the other)

• But the second option

intuitive to clean...

is easier/more

derivative" images ("nterms>1", the Sault &



WSClean's Multi-frequency clean algorithm: (1 maj iter)

- Make residual images at different frequencies
- Start cleaning:
 - Find a peak in the **integrated** image
 - Measure the flux at this position in the subband images
 - Subtracted the correct PSF from each subband image.
- ...Until major iteration threshold is reached
- (Optionally) convert to Taylor-term images and predict

WSClean's Multi-frequency clean algorithm: (1 maj iter)

- Make residual images at different frequencies
- Start cleani
- This is called "joined-channel cleaning"
 - in WSClean
- Meas

- Find a

the subband

le

- ima (Offringa and Smirnov. 2017)
- Subtracted the concerned non-cach subband image.
- ...Until major iteration threshold is reached
- (Optionally) convert to Taylor-term images and predict

WSClean's Multi-frequency clean algorithm: (1 maj iter)

• Make residual images at different frequencies



Multi-scale kernel



Figure 1. Shape functions for scales $\alpha = 64$ pixels and $\alpha = 128$ pixels.

Fast multi-scale deconvolution

- In Cornwell's (2008) multi-scale method, the appropriate scale is determined every minor iteration
- Cornwell's algorithm can be sped up by keeping the scale fixed "for a while"
- This is the algorithm implemented in WSClean



(d) Multi-frequency single-scale clean (residual RMS=460 μ Jy/PSF)



- Comparison of WSClean MF single scale and multi-scale cleaning
- Simulated bandwidth of 30 MHz at 150 MHz.
- MWA layout, 2 min snapshot

Offringa and Smirnov (2017)

Deconvolution performance

Deconvolution speed





Figure 12. Example of the progression over time when using the new multiscale clean algorithm on a 2048×2048 image.

Offringa and Smirnov (2017)





(a) Original



(e) WSCLEAN model



(b) Convolved image (σ =640,000 units/PSF)



(f) WSCLEAN residual (σ =15 units/PSF)



Compressed sensing results



(d) WSCLEAN + MORESANE

- "Moresane" compressed sensing deconvolution (A. Dabbech et al. 2014)
- Multi-frequency implementation in WSClean
- Produces sometimes very good-looking models

Model(!) image made with WSClean + Moresane

Offringa and Smirnov (2017)

An issue with IUWT / Moresane...



(a) WSCLEAN multi-frequency, multi-scale with β =0.6 (b) WSCLEAN multi-frequency, iuwt (rms=2,7 mJy) (rms=1.4 mJy)

Offringa and Smirnov (2017)

Automatic scale-dependent masking

- Normal cleaning requires manual threshold tweaking, manual masking, etc...
- Masking is hard when structures are diffuse
- Move towards non-interactive, fully automatic cleaning
- "Automatic scale-dependent masking" :
 - For each scale, a mask is accumulated
 - Clean normal to 3-5σ, continue to 0.5σ with a scale-dependent mask. In one run.

Automatic masking

- Threshold is relative to RMS estimate
- RMS estimate can be "local" when RMS is expected to change over the image (avoids picking up calibration errors)
- Avoids interaction & somewhat-arbitrary selection of features, etc.
- Allows deeper & more stable cleaning of complex structures. Limits clean bias.
- Can be done in multi-frequency mode

Auto-masking on point sources



Auto-masking on point sources



Auto-masking on point sources



Automasking VLBI example



Restored

Residual

Data by J. P. McKean and C. Spingola



(a) Multi-scale model image without masking

(b) Multi-scale model image with automatic masking



(c) Multi-scale residual without masking (rms=50 mJy/B)

(d) Multi-scale residual with automatic masking (rms=38 mJy/B)



Figure 9. Automatic scale-dependent masking applied on the UGC12591 test-set.



J2000 Right Ascension

Reasons for adding more constraints in DD calibration

- LBA calibration
 - See talk by Francesco later today
 - No current pipeline can produce (good) DD solutions
- HBA diffuse imaging
 - Current pipelines calibrate diffuse structures out
- EoR imaging
 - Constraints important to avoid reducing EoR signals
- "Normal" deep HBA imaging
 - Interpolated TEC screens to get solutions with more accurate solutions





Collaboration with Dijkema, Offringa, Gasperin, Mevius, van Weeren, et al.

Local RMS cleaning



Local RMS cleaning



Modeling with WSClean

- WSClean (since 2.4) can directly output a beam corrected calibration model
- Consists of point sources, Gaussians and spectral information
- Directly readable by DPPP (T.J. Dijkema)
 - Allows DD calibration with WSClean + DPPP
- Local RMS method reduces false components

Summary

- WSClean provides fast gridding & deconvolution
 - WSClean multi-scale with joined channels
 >2 order of magnitude faster than CASA MSMFS mode.
- Fully automated cleaning
 - Thresholds given in sigma's, not in Jy.
- Auto-masking improves accuracy / clean bias
- Can directly output point-source & Gaussian model including frequency information
- Next upgrade: WSClean + IDG + A-term correction

Download WSClean incl. manual from: <u>http://wsclean.sourceforge.net/</u>