Post-processing for High-Contrast Imaging: ground-based instruments





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Direct imaging with ground-based telescopes



Wednesday 11.00am J.-B. Ruffio



Friday 11.00am Steph Sallum

Friday 8.30am Guillaume Bourdarot



Direct imaging with ground-based telescopes





Ground based telescopes (8-m class) Near - thermal infrared (H-band, 1.6µm to N-band, 10µm)

High-dynamic



High-contrast imaging

High Angular resolution few milliarcseconds & High Contrast more than 10-6









High-contrast imaging









Bright starlight residuals !



Light-rays **interfere** in the focal plane



Summary of our task



Thursday 11am Julien Milli

Tailored image processing techniques to carve out the residual starlight —> 10-6 contrast

What do we want / need:

- **Detection**: discriminate H_0 from H_1 + confidence level
- Characterisation: astrometry & photometry + uncertainties
- **Detection limit**: algorithm performance (astro-centered)
- **Comparison**: apply different algorithms (algo-centered)
 - Maximizing True positives, minimizing False negatives
- For point source (substellar companions) & extended source (circumstellar disks)





Differential imaging 101

Find a different behaviour between (1) the astrophysical signals

Exploit this **diversity** to recover the signal !





This step is critical !!!

Whitens the residuals !

and (2) the starlight residuals





Differential imaging 101

Need a specific observing strategy & calibration procedure Provide with various diversities

> **Binary** Differential Imaging: Rodigas et al., 2015 Ruane et al. 2019 **Polarimetric** Differential Imaging: Kuhn et al. 2001

Reference Differential Imaging: Mawet et al., 2009, Rameau et al. 2012 multi-Reference Differential Imaging: Xuan et al. 2018, Bohn et al. 2019, **Spectral** Differential Imaging: Racine et al. 1999, Sparks and Ford 2002 Coherence Differential Imaging: Baudoz et al. 2005 Angular Differential Imaging: Marois 2006, Davies 1980

Focus on ADI-based techniques !

 $\bullet \bullet \bullet$

Angular Differential Imaging

Pupil tracking mode:

For an alt-az mount telescope Disable the field derotator



Observing time

Pupil field Optics / wavefront remain in the same direction

It brings angular diversity

ADI is a technique, not an observing mode or data set type

Observing time

Image field Field of view rotates w/ parallactic angles

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1.Estimating the star image The basic approach

Pairwise subtraction:

The closest frames in time are the most correlated while not self-subtracting the signal



frame (t1)



frame (t2)



The optimal $\Delta \alpha$ is **0.5 lambda/D**



Temporal median:

The median represents the 'typical' image while the moving signal is not taken into account

Marois et al., 2006



Temporal median



frame (t1) -median



It comes with various flavours: smart-ADI, annular-ADI And variations: Image Rotation Subtraction Dou et al., 2015





1. Estimating the star image The classic approach

Principal Component Analysis (PCA): Linear combination of the images of the cube

decomposed over orthogonal basis (eigen-images)

Soummer et al., 2012

Amara & Quanz 2012



And also... smart-PCA, Absil et al., 2013 LLGS, Gonzalez et al., 2016 AMAT, Daglaya et al., subm. NMF, Ren et al., 2018 Space-Time KLIP, Lewis et al., 2023



Locally Optimized Combination of Images (LOCI): Find the linear combination that minimises the residuals while the moving signal is not taken into account Lafrenière et al., 2007 Model ! Min(σ_{res}^2) = Min $\sum m_i$ **Binary mask** Coefficients All the images (t) Images And also... Template-LOCI, Marois et al., 2014 Adaptive-LOCI, Currie et al., 2012 Matched-LOCI, Wahhaj et al., 2015 Damped-LOCI, Pueyo et al., 2016



1. Estimating the star image Half Sibling Regression



Gebhard et al., 2022

Exclusion region





1. Estimating the star image Signal Safe Speckle Subtraction (4S)



Explainable Machine Learning







AF Lep b (2011)



Auto-Grad against signal loss

Bonse et al., 2024



2. Residuals after subtraction

Also called 'subtraction residuals', 'differential imaging' residuals, 'post-processing residuals'

The noise distribution of the residuals is sub-exponential (and not Gaussian) > hence the high number of false positives !





2. Residuals after subtraction Beyond the 5- σ contrast curve for non-Gaussian noise

1. Observation & Measurement





 $SNR = T_{obs} = 2.28$







Jensen-Clem et al., 2017

Bonse et al., 2022

3. Statistical Test & Conclusion

It is essential to have a realistic estimate of the distribution of the residual noise **Confidence** level





3. Combining the images

Mean combination



There is no formal proof that one is better than the other...



Median combination



3. Combining the images

Noise weighted combination

Bottom et al., 2017

Optimal weight
$$F_{opt} = rac{1}{\sum_i rac{1}{\sigma_i^2}} \sum_i rac{F_i}{\sigma_i^2}$$

Pairet et al., 2019

STIM =
$$\frac{\hat{\mu}_g}{\hat{\sigma}_g}$$

Normalization factors to optimize SNR

Empirical normalisation



Statistical testing

Mawet et al., 2014

Accounting for small-sample statistics

Similar to adapting the threshold

Multinest approach

Golomb et al., 2020

Nested sampling to compute the evidence for H0 and H1.

SNAP approach

Thompson & Marois, 2021

Optimisation of the S/N ratio

Balance noise reduction vs. self-subtraction



3. Combining the images

STIM Largest Intensity Mask (SLIMask):

Pairet et al., 2021 (PhD thesis)



Mask to apply on STIM-maps: Average location of the largest entries for a range of ranks



Regime Switching Model (RSM):

Dahlqvist et al., 2020, 2021ab, 2022



Build a time series in residual cubes: Probability of H₁ at t, knowing state at t-1













4. Detection map Supervised binary classification

Supervised exOplanet detection via Direct Imaging with deep Neural Networks (SODINN)

Binary Classifier after a PCA subtraction



Gomez Gonzalez et al., 2018



Noise Adaptative SODDIN (NA-SODINN)

Add SNR curves to support the training process











Characterization of the point-sources

Forward Modeling

(inclusing assumption on noise distribution)

1. Estimate the star image





Negative Fake Companion injection (NEGFC) + minimization

direct SNR map estimate $SNR = f_p / \sigma(f_p)$

Forward Modeling of the planetary signal Basic concept Also called "inverse problem" or "Match Filtering" approach



Maximum likelihood estimation:

$$L(r_0, a) \propto exp\left(-\frac{1}{2} \left\|\frac{\Delta(r, k) - a p(r, k; r_0)}{\sigma_{\Delta}(r)}\right\|$$

ANDROMEDA

Mugnier et al., 2009

Cantalloube et al., 2015







Forward Modeling of the planetary signal Better subtraction ?



Image at t₁



Linear Combination of first PCs



Maximum likelihood estimation:

$$L(r_0, a) \propto exp\left(-\frac{1}{2} \left\|\frac{\Delta(r, k) - a p(r, k; r_0)}{\sigma_{\Delta}(r)}\right\|$$

FMMF

Pueyo et al., 2016

Ruffio et al., 2017



Forward Modeling of the planetary signal Better differential residuals model?

r-ANDROMEDA

Cantalloube et al., subm. in 2019

Forward Modeling of the planetary signal Not even subtraction ?

H₁: model planet signature h off-axis PSF

H₀: model of the background f Multivariate Gaussian

Maximum likelihood estimation with multivariate Gaussian noise:

$$\mathrm{p}_f(\{m{f}_{\lfloor \phi_t
ceil,t}\}_{t=1:T}) = \prod_{t=1}^T \mathcal{N}ig(m{f}_{\lfloor \phi_t
ceil,t} ig|m{m}_{\lfloor \phi_t
ceil}ig)$$

PAtch COvariance (PACO)

Flasseur et al., 2018

Empirical mean <u>and</u> covariance on temporal patches

 $_{\downarrow]}, \mathbf{C}_{\lfloor \phi_t
bracket}$

Forward Modeling Temporal Reference Analysis of Planets (TRAP)

Temporal PCA model of the starlight + Forward Modeling

Samland et al., 2021

Penguin interlude

That's a lot !

Exoplanet Imaging Data Challenge a community-wide effort

- Started in 2019!
- First phase launched in Sept. 2019 Workshop HCI post-processing, Berlin, Germany
- First phase closed in Oct. 2020
- Publication SPIE 2020
- Second phase (characterization) launched Apr. 2022 Third phase (disk imaging) for ~2025 Fourth phase (high resolution spectroscopy) for ~2026

https://exoplanet-imaging-challenge.github.io/

Post-processing techniques performance assessement

Gomez Gonzalez et al., 2016

Counting True and False positives

Detection map + threshold + posterior (spectro)-photometry

- True positive rate: TPR = TP/(TP+FN)
- False discovery rate: FDR = FP/(FP+TP)
- False positive rate: FPR = FP/(FP+TN)

At the submitted threshold, we compute:

• F1-score = 2 TP / (2 TP+FP+FN)

SADI-based characterization: Data type

Multispectral image cube

(spectro)-photometryAstrometry

1. Astrometry of point sources

Х

Thursday 9.15am Sarah Blunt

Final "ranking"

Method	PCA-NEGFC			ANDROMEDA		
	planet b	planet c	all	planet b	planet c	all
Astrometry	0.37	0.03	0.20	1.95	0.06	1.01
Spectro-photometry	16.98	1.03	9.00	35.67	2.29	18.99

EIDC	websi
EIDC	websi

Penguin interlude #2

Circumstellar extended structures: Protoplanetary disks and debris disks

Garuffi et al., 2017

Total intensity image in IR:

- Face-on circular disks
- Structures on edge-on disks
- Spiral structure
- Shadows, dips, gaps...
- Disentangling planets-disks

Towards EIDC Phase 3 !

Classic approaches

Breaking down optimisation regions enforcing positivity and sparcity

Model Classical 75°

NMF

KLIP

Mask the signal Analyse the ADI-made distortion

Milli et al., 2012 Ren et al., 2020a

Stapper & Ginsky, 2022

Iterate the ADI subtraction to minimize self-subtraction

Pairet et al., 2018

Image reconstruction approaches

MAYONNAISE

Pairet et al., 2020

Morphological Component Analysis: -Disk in shearlet space -Planet in direct space

Mask the ambiguous region due to rotation (not known)

MUSTARD

Juillard et al., 2023

REXPACO

Flasseur et al., 2021

PACO framework to estimate noise Iterates on the disk estimation

To go further ! Building the reference PSF multi-Reference RDI: Using a library of images as a database Using Data Imputation with NMF Ren et al., 2018 Using Structure Similarity Index Ruane et al., 2019 ConStruct (Auto-encoders based) Wolf et al., 2023 Data Imputation Poster #27 Sandrine Juillard with semi-supervised CNN Juillard et al., 2024 **Poster #8** Cao Fangyi IPCA: Combine ADI + RDI

Observing strategies for RDI: Using another reference star

Snapshot of similar targets

Star-hopping observations

Wahhaj et al. 2021

Poster #32 Pengyu Liu

Poster #47 Richelle Cvan Capelleveen

To go further ! Building the reference PSF

Estimation with an instrumental model

Poster #18 Rodrigo Ferrer-Chavez

Pipelines

- Preprocessing tools
- Library of post-processing algo PCA, LOCI, ANDROMEDA, PACO
- Characterization tools NEGFC, MCMC...

Library of algorithms ! https://vip.readthedocs.io

PyKLIP

- Ready-made configuration GPI, CHARIS, SPHERE, NIRC2, VisAO
- Characterization FM (disk incl.)

 Post-processing algo + detection maps KLIP, mRDI + *planetevidence* (multinest)

- Complete toolbox FM-based
 - https://pyklip.readthedocs.io

- Preprocessing tools w/ pre-configuration files SPHERE, NaCo
- Post-processing algo PCA mainly, in-house PACO...
- Characterization tools NEGFC, MCMC...
 - Large data sample management !
 - https://pynpoint.readthedocs.io
- And also, CHARIS, GRAPHICS, SPHERE-DC, Data Cruncher etc. You can use all these beautiful tools !

Summary of key points: post-processing is essential to gain > 1mag

- Understanding the limitations of HCI: temporal stability is key
- Relies on specific observing strategies and calibration
- Characterising the starlight residuals and differential residuals distribution
- All algorithm provide different outputs requiring different interpretation • Assessing the performance is <u>not</u> obvious at all
- Data challenges are a great tool for homogeneous comparison

Advanced post-processing techniques are available and documented ! Use several concept to achieve better astrophysical input

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