Deep learning for exoplanet detection and characterization by direct imaging at high contrast

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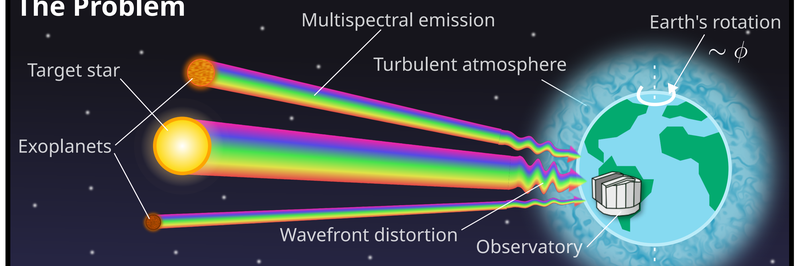
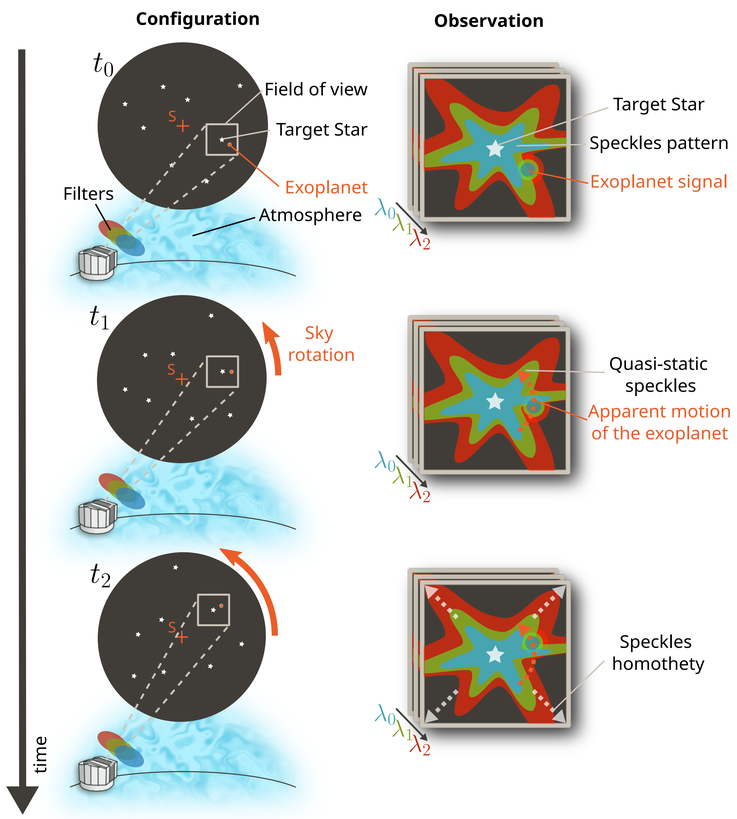
The Problem



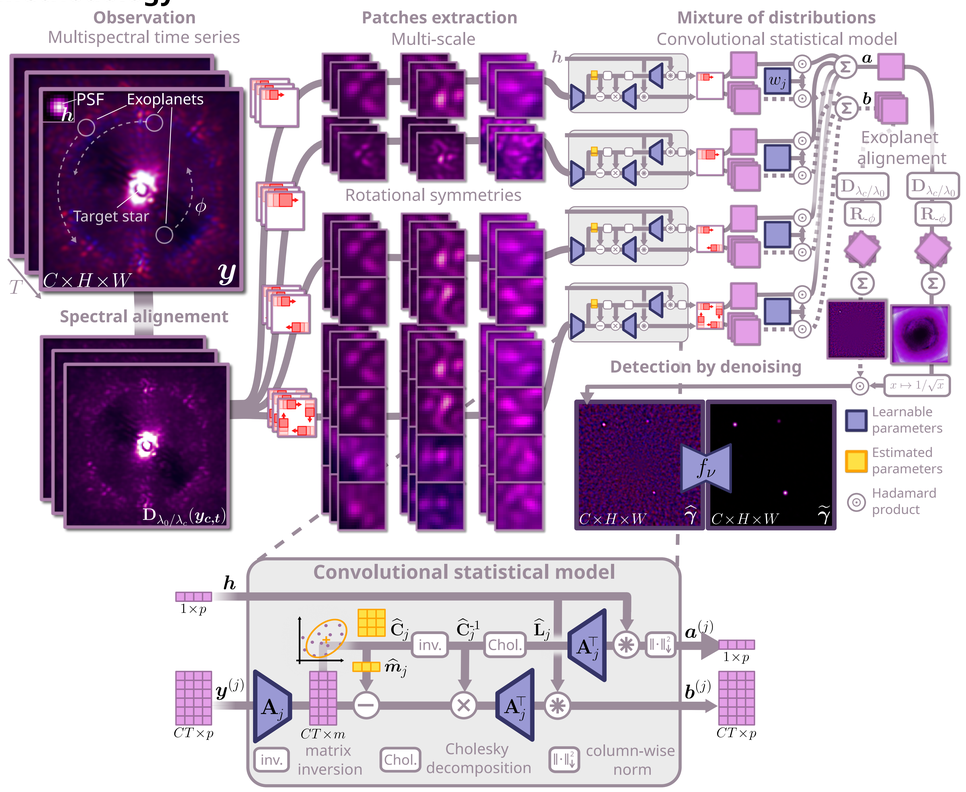
- Direct imaging of exoplanets is challenging because of:
  - the high angular resolution required,
  - the high contrast between the brightness of the target star and exoplanets.
- In addition, the signals of exoplanets are obscured by the glare of the star, or "speckle pattern", which is primarily caused by wavefront distortion in the Earth's atmosphere.

Image Formation Model



- The natural rotation of the Earth causes an apparent motion of the exoplanet signal, while speckles remain quasi-static.
- Because of diffraction, the relationship between speckle patterns at different wavelengths can be approximated by a homothety.

Methodology



The proposed architecture recovers the **flux** of exoplanets by solving:

$$\widehat{\boldsymbol{\alpha}} = \underset{\boldsymbol{\alpha} \in \mathbb{R}^{H \times W}}{\arg\min}\ \underbrace{\varphi_\theta(\boldsymbol{\alpha}, \chi(\boldsymbol{y}))}_{\mathbf{A}} + \underbrace{\psi_\nu(\boldsymbol{\alpha})}_{\mathbf{B}}$$

A. Learnable prior on the **speckles**: our **convolutional statistical model** combines distributions at multiple scales, joint spectral modeling, and physics-based symmetries. The objective function writes:

$$\varphi_\theta(\alpha, \boldsymbol{x}_0, \chi(\boldsymbol{y})) = \prod_t \prod_{j \in S(\boldsymbol{x}_t)} \mathbb{P}\left(\mathbf{A}_j\left(\boldsymbol{y}_t^{(j)} - \alpha \boldsymbol{h}^{(j)}(\boldsymbol{x}_t)\right) \mid \widehat{\boldsymbol{m}}_j, \widehat{\mathbf{C}}_j\right)^{w_j}$$

and admits a closed-form optimum:

$$\widehat{\alpha} = \frac{\sum_t b_t(\boldsymbol{x}_t)}{\sum_t a_t(\boldsymbol{x}_t)} \qquad \widehat{\sigma}_\alpha = \frac{1}{\sqrt{\sum_t a(\boldsymbol{x}_t)}}$$

where:

$$a(\boldsymbol{x}_t) = \sum_{j \in S(\boldsymbol{x}_t)} w_j\, \boldsymbol{h}^{(j)}(\boldsymbol{x}_t)^\top \mathbf{A}_j^\top \widehat{\mathbf{C}}_j^{-1} \mathbf{A}_j\, \boldsymbol{h}^{(j)}(\boldsymbol{x}_t)$$

$$b_t(\boldsymbol{x}_t) = \sum_{j \in S(\boldsymbol{x}_t)} w_j\, \boldsymbol{h}^{(j)}(\boldsymbol{x}_t)^\top \mathbf{A}_j^\top \widehat{\mathbf{C}}_j^{-1} (\mathbf{A}_j \boldsymbol{y}_t^{(j)} - \widehat{\boldsymbol{m}}_j)$$

B. Learnable prior on the **exoplanet signal**: implemented by denoising the detection map ($\widehat{\gamma} = \widehat{\alpha}/\widehat{\sigma}_\alpha$) resulting from **A**.

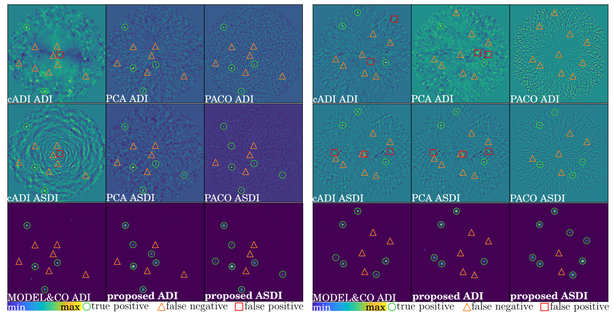
The architecture is trained end-to-end, by injecting synthetic exoplanets into real observations, and maximizing the log-likelihood of the predicted flux.

Results

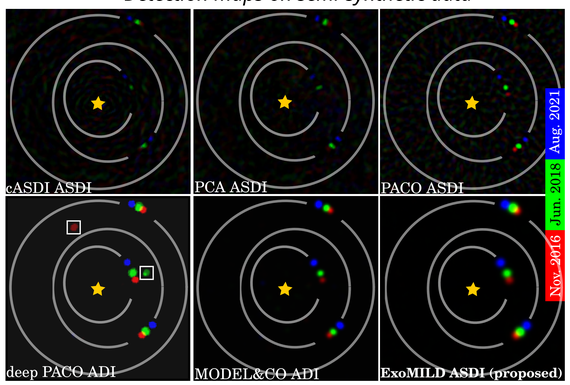
Detection performance

	Method	HD159911 (54°)	HD216803 (23°)	HD206860 (11°)	HD188228 (6°)	HD102647 (2°)	average AUC
Monospectral	cADI	0.288 ± 0.014	0.422 ± 0.007	0.489 ± 0.010	0.303 ± 0.014	0.343 ± 0.009	0.369 ± 0.005
	PCA	0.634 ± 0.010	0.643 ± 0.011	0.505 ± 0.009	0.392 ± 0.011	0.218 ± 0.011	0.478 ± 0.005
	PACO	0.629 ± 0.006	0.669 ± 0.012	0.579 ± 0.015	0.517 ± 0.015	0.207 ± 0.012	0.520 ± 0.006
	MODEL&CO	0.653 ± 0.010	0.731 ± 0.011	0.646 ± 0.012	$\mathbf{0.638} \pm 0.014$	$\mathbf{0.554} \pm 0.009$	$\mathbf{0.645} \pm 0.005$
	Proposed	$\mathbf{0.673} \pm 0.009$	$\mathbf{0.740} \pm 0.010$	$\mathbf{0.661} \pm 0.012$	0.631 ± 0.013	0.518 ± 0.012	$\mathbf{0.645} \pm 0.005$
Multispectral	cASDI	0.448 ± 0.009	0.537 ± 0.013	0.451 ± 0.007	0.352 ± 0.017	0.294 ± 0.012	0.417 ± 0.006
	PCA	0.694 ± 0.013	0.696 ± 0.007	0.552 ± 0.011	0.398 ± 0.011	0.236 ± 0.009	0.515 ± 0.005
	PACO	0.698 ± 0.015	0.768 ± 0.008	0.710 ± 0.014	0.700 ± 0.009	0.589 ± 0.014	0.693 ± 0.005
	Proposed	$\mathbf{0.731} \pm 0.009$	$\mathbf{0.804} \pm 0.013$	$\mathbf{0.747} \pm 0.010$	$\mathbf{0.782} \pm 0.008$	$\mathbf{0.744} \pm 0.006$	$\mathbf{0.761} \pm 0.004$

AUC-ROC evaluated on semi-synthetic data



Detection maps on semi-synthetic data



Detection maps obtained on real exoplanets (HR 8799 system)

Characterization performance

Method	flux error (ARE)	position error (RMSE)
PACO	0.56	0.21
Proposed	**0.51**	**0.11**

[1] Bodrito+ "MODEL&CO: Exoplanet detection in angular differential imaging by learning across multiple observations" MNRAS 2024.
[2] Flasseur+ "Exoplanet detection in angular differential imaging by statistical learning of the nonstationary patch covariances" A&A 2018.
[3] Marois+ "Angular differential imaging: a powerful high-contrast imaging technique" A&A 2006.