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SpeckleNet: a deep learning framework to improve detection sensitivity of giant planets

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The atmospheric characterization of giant exoplanets has so far relied primarily on transit spectroscopy, a technique intrinsically biased toward short-period planets and therefore largely inaccessible for cold, long-period giants. High-contrast imaging (HCI) fills this gap by providing a complementary route to study the atmospheres of wide-orbit giant planets directly. However, conducting blind HCI surveys at scale remains extremely expensive in terms of telescope time, making target selection a critical bottleneck for atmospheric characterization. The upcoming Gaia DR4, together with long-period radial-velocity surveys such as CORALIE, will fundamentally change this landscape. For the first time, we will have a well-defined and statistically significant sample of giant planets identified through RV and astrometry alone. This enables a new observational strategy: instead of broad HCI surveys, we can concentrate direct imaging efforts on golden targets, where dynamical signatures already predict the presence of giant planets at separations accessible to direct imaging. In this scenario, maximizing HCI sensitivity becomes essential. While HCI instrumental upgrades (e.g., SAXO+) continue to improve raw performance, image post-processing techniques remain equally crucial. Among these, Principal Component Analysis (PCA) has long been the community standard due to its computational efficiency and strong mathematical foundation. Yet recent studies have revealed fundamental limitations, including its restriction to linear correlations and significant planet self-subtraction (Bonse et al. 2024). To mitigate these issues, multiple alternatives have been proposed, ranging from PCA refinements to machine-learning based classifiers for enhanced detection (e.g., Cantero et al. 2023). More recently, developments in generative models have demonstrated particularly strong potential. For instance, the ConStruct algorithm (Wolf et al. 2024) replaces PCA with a convolutional autoencoder (AE) at modeling image noise, achieving deeper detection limits on Keck/NIRC2 data and providing a compelling proof-of-concept for deep generative approaches in HCI. In this context, the growing availability of large-scale HCI datasets from surveys, the rapid progress in generative model architectures, and the improved understanding of speckle noise gained in recent years now converge to enable more powerful approaches for improving detection sensitivity. To harness this potential, we introduce SpeckleNet, a deep learning framework for high-fidelity, instrument-based speckle modeling. SpeckleNet explores modern generative architectures, including variational AEs, diffusion models, andothers, trained on extensive HCI datasets. The framework also employs conditional learning, allowing adaptation to atmospheric conditions. In this work, we present the first SpeckleNet release and demonstrate its ability to enhance sensitivity and recover known substellar companions in VLT/SPHERE data. Looking ahead to Gaia DR4 and ongoing CORALIE monitoring, SpeckleNet provides a powerful computational tool to fully exploit the upcoming population of dynamically identified giant planets, enabling targeted HCI follow-up and a more complete atmospheric census at wide separations.

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