Removing cloud shadows from ground-based solar imagery

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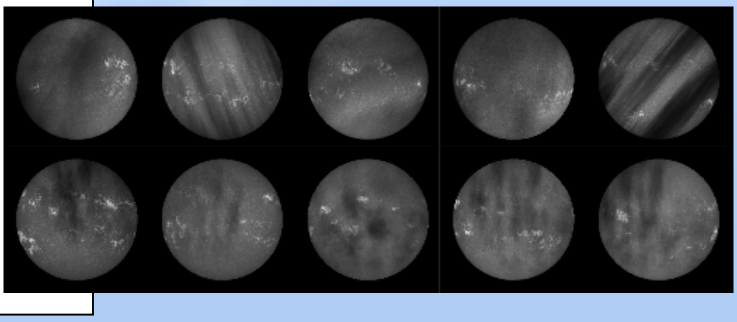
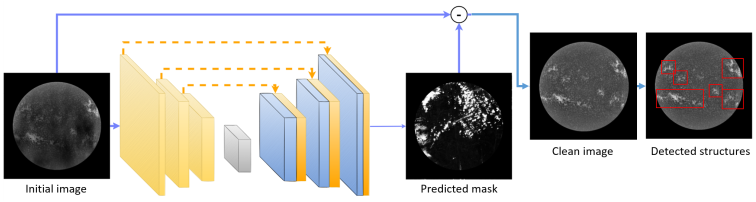
Abstract

All ground based observatories face a same problem: images may be polluted by terrestrial clouds. These clouds are often thin, due to no observations being usually performed in case of thick clouds. We propose a new method to remove these cloud shadows, based on deep learning. We evaluate our method on Ca-II and H-α images from three different observatories, and a new dataset of synthetic clouds applied to real observations. Quantitative assessments are obtained through various image restoration quality metrics in a first instance, then through quantifying the enhanced automatic filament detection.

We demonstrate improved results with regards to the traditional cloud removal technique, on different cloud types and textures. Faster computation times are also obtained.



Methodology



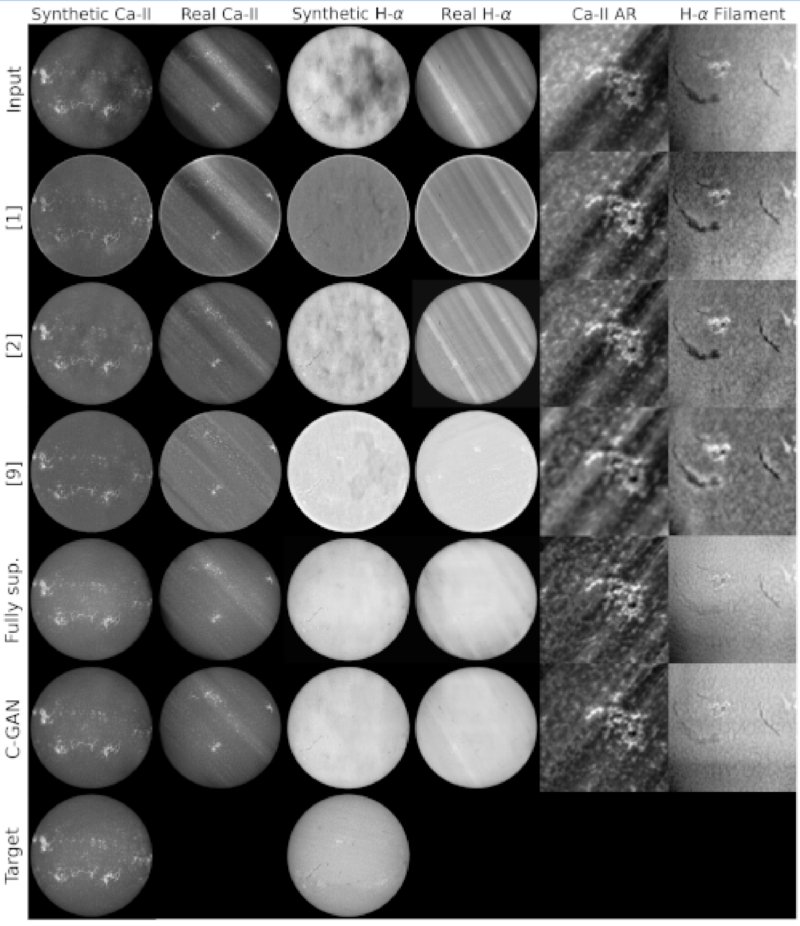
We investigated deep learning methods for removing large cloud shadow contaminants from ground-based solar imagery I_{ini} to create a cleaned image ($\hat{I}_{\text{clean}}$). We adopted the U-Net-style architecture for more detailed outputs. We compared three possible inference methods, and two training setups: fully-supervised and C-GAN.

We experiment with our DNNs predicting either the cleaned image directly, or a cloud shadow mask $\hat{M}$ as:

$$\hat{I}_{\text{clean}} = \frac{I_{\text{ini}}}{\hat{M} + \epsilon}$$

with an alternative implementation \ie adding in the intensity that was removed by clouds. This is similar to predicting a residual mask:

$$\hat{I}_{\text{clean}} = I_{\text{ini}} + \hat{M}$$

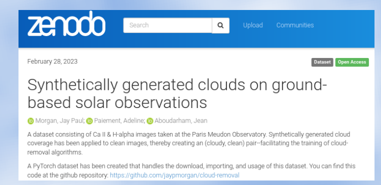


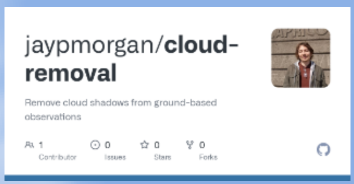
Data	Method	PSNR ↑	SSIM ↑	RMSE ↓
Ca-II	[1] (15 failures)	21.90	94.8	8.6
	[2]	26.0	98.1	5.4
	[9]	23.2	92.7	7.3
	Fully sup.	**30.6(0.3)**	**98.9(0.1)**	**3.7(0.1)**
	C-GAN	30.0(0.4)	98.8(0.2)	3.9(0.1)
H-α	[1] (5 failures)	14.8	91.4	19.6
	[2]	23.3	98.4	7.0
	[9]	21.0	96.0	9.2
	Fully sup.	**28.6(0.3)**	**98.9(0.1)**	**4.5(0.2)**
	C-GAN	28.3(0.5)	98.9(0.2)	4.6(0.2)

Results

The DNNs obtained better results than the domain's SoTA and a non-leaning method based on sparse approximation, with better restoration of the underlying solar structures, and are the new SoTA. The training setups have different strengths and weaknesses: full supervision produces more homogeneous solar disks, and C-GAN better handles strong clouds. Future work may further focus on filament restoration, and evaluate the effect of cloud removal on a subsequent image analysis e.g. the automatic detection of solar structures.

All data and models are publicly available at github.com/jaypmorgan/cloud-removal and https://zenodo.org/record/7684201





References:
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This work was funded by ANR grant N° ANR-20-CE23-0014-01. JA thanks CNES (Centre National d'Etudes Spatiale, the French space agency) for its support in this project.