SOLAR ACTIVE REGIONS LOCALIZATION OVER MULTI-SPECTRAL OBSERVATIONS

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Context

Active regions (AR) play an important role in understanding solar activity and space weather. Their localization (i.e. detection and segmentation) is a key step in studying their spatio-temporal evolution.

ARs are 3D objects, imaged at different layers of the solar atmosphere. Previous works, e.g. [1], did not consider this 3D aspect and only did 2D localization.

Deep learning achieves state-of-the-art detection and segmentation on multi-spectral data. However, these methods:

- produce a single localization for all image bands,
- do not apply to the case of images showing different layers of a 3D AR,
- require manual annotations for training, particularly costly for segmentation.

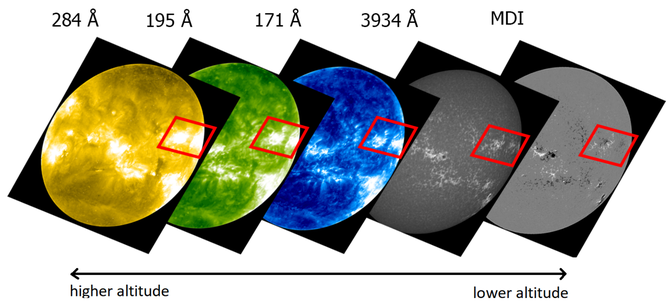


Fig. 1: A 3D active region seen in several layers of solar atmosphere.

Data and annotation

- We use images and magnetograms from SOHO/EIT & MDI (space based), and the Paris-Meudon Spectroheliograph (PM/SH) (ground based).
- Images are time-matched and span a full solar cycle.
- Simple manual annotations are produced to train ML algorithms, as tight bounding boxes around ARs.

Dataset	Modality	resolution	Obs. frequency	# images	# BBoxes
EIT	SOHO/EIT 284 Å	1024x1024	12 min	323	1711
	SOHO/EIT 171 Å	1024x1024	12 min	323	1735
	SOHO/EIT 195 Å	1024x1024	12 min	323	1572
Meudon	PM/SH 3934 Å	1500x1340	∼ 1 day	266	1786
	SOHO/MDI magnetogram	1024x1024	96 min	266	1786

Tab. 1: Technical summary of our two annotated datasets

Proposed AR localization

Our proposed framework:

- uses multiple branches to jointly analyze different image bands,
- accounts for the interdependencies between the bands for a better accuracy.

Multi-spectral AR detection

SR-CNN [2] based on a Faster R-CNN [3] backbone:

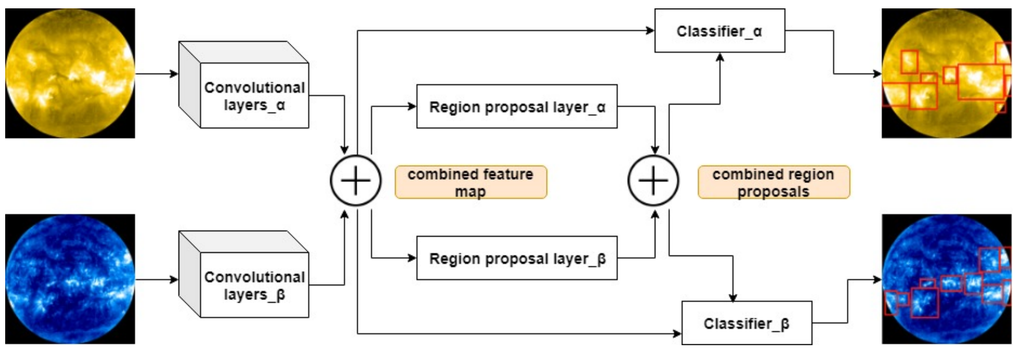


Fig. 2: SR-CNN's architecture

Multi-spectral AR segmentation

- SUNet based on the UNet [4] backbone,
- trained from **weak labels** (i.e. bounding boxes).

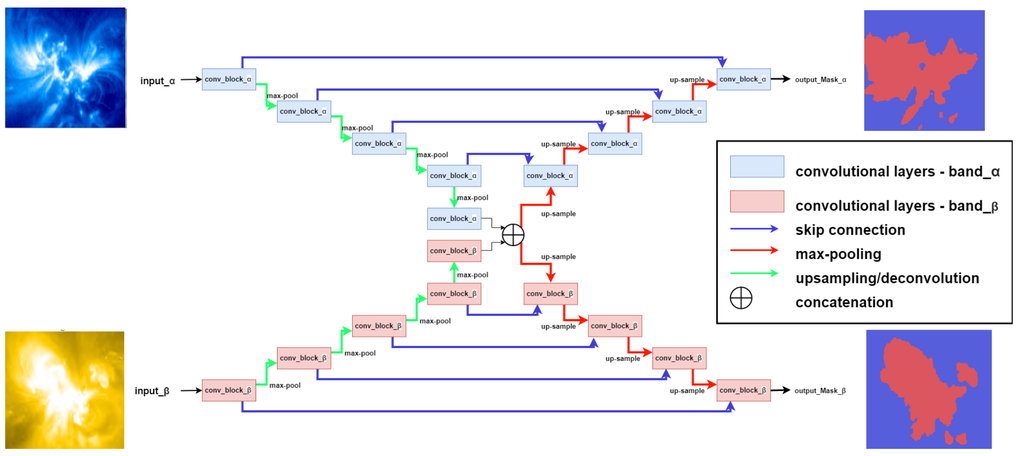


Fig. 3: SUNet's architecture

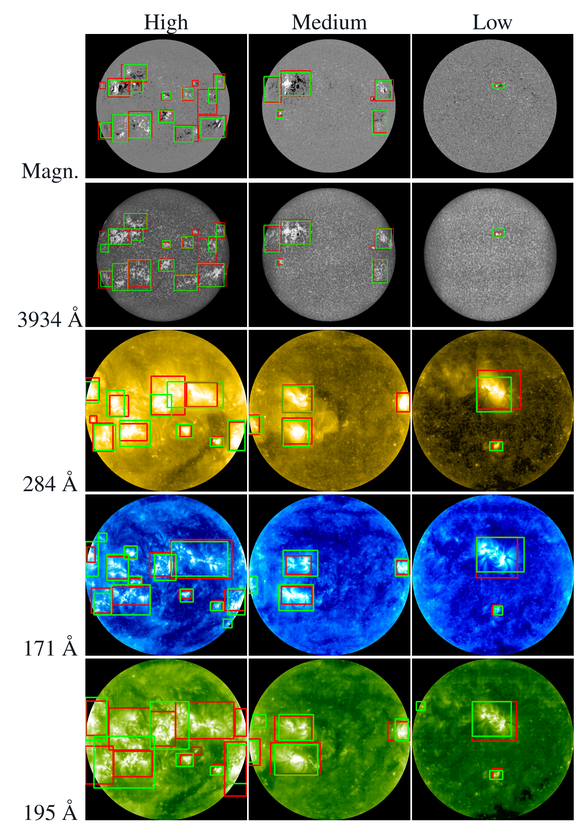
Results

Detection:

- SR-CNN achieves a better precision and F1-score than state-of-the-art SPOCA.
- Jointly analyzing two image bands tends to improve on single band analysis.

Method	Dataset	Modality	Precision	Recall	F1
SPOCA	SPOCA	171 Å	0.44	0.95	0.60
	subset of EIT	195 Å	0.50	0.97	0.66
SR-CNN	SPOCA	171 Å	0.80	0.95	**0.87**
	subset of EIT	195 Å	0.88	0.95	0.91
	EIT	171 Å	0.84	0.95	**0.89**
		195 Å	0.87	0.95	**0.91**
	EIT	171 Å	0.89	0.92	**0.90**
		284 Å	0.88	0.91	**0.89**
	Meudon	3934 Å	0.96	0.81	**0.88**
		Magnetogram	0.93	0.79	0.85
FR-CNN	EIT	171 Å	0.88	0.88	0.88
		195 Å	0.91	0.91	**0.91**
		284 Å	0.86	0.88	0.87
	Meudon	3934 Å	0.82	0.83	0.83

Tab. 2: Detection performance comparison against SPOCA [1] and the single image analysis of Faster R-CNN [3].



Tab. 3: Detection results (green) against ground-truth (red). Rows: modalities, columns: solar activity level.

Segmentation:

- SUNet achieves competitive segmentation from weak labels.
- Comparative evaluation currently in progress.

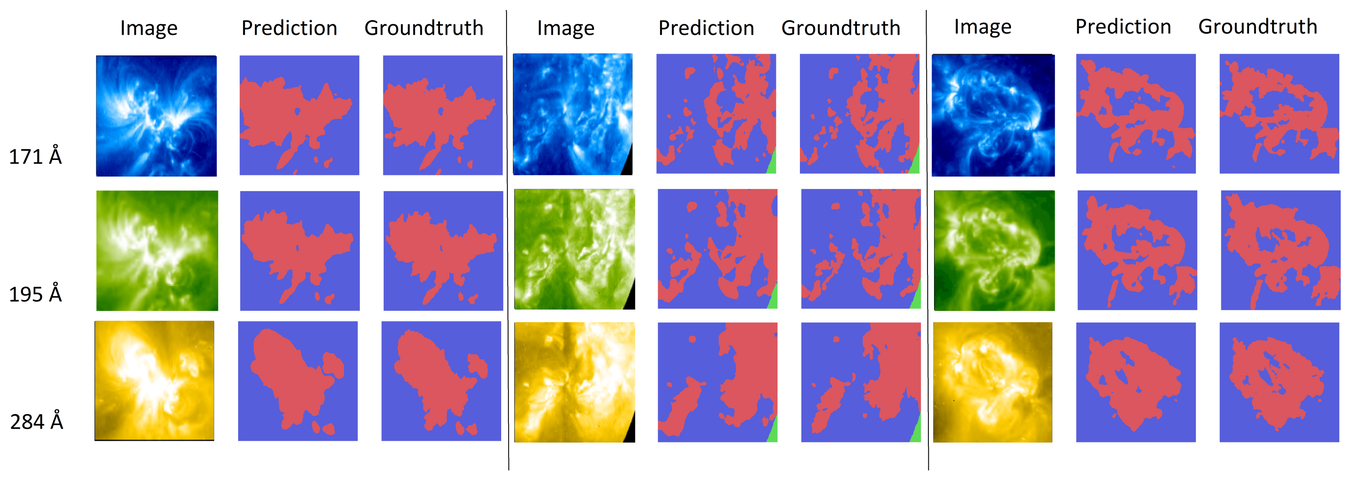


Fig. 4: Segmentation results.

References

[1] C. Verbeeck, V. Delouille, B. Mampaey, and R. De Visscher. The SPoCA-suite: Software for extraction, characterization, and tracking of active regions and coronal holes on EUV images. Astronomy & Astrophysics, 561, 2013.

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[3] S. Ren, K. He, R. Girshick, and J. Sun. Faster R-CNN: Towards real-time object detection with region proposal networks. In NIPS, 2015.

[4] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-Net: Convolutional Networks for Biomedical image segmentation. MICCAI, 2015.

Conclusion

We propose a new deep learning framework for AR localization that:

- analyzes all image bands *jointly*, taking into account their *interdependencies*,
- produces one localization per image band, in line with the 3D nature of the data,
- fits both detection and segmentation paradigms,
- may naturally accommodate any number of image bands simultaneously,
- requires no manual intervention, and only weak labels at training, to detect and finely segment ARs.