SPODIfY: Space Plasmas Object Detection Inspired from YOLO

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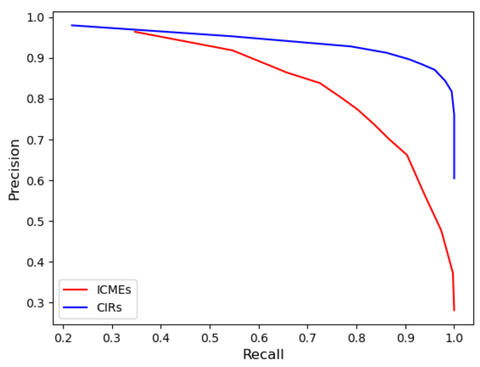
Interplanetary Coronal Mass Ejections (ICMEs) and Co-Rotating interaction regions (CIRs)

- Known to be among the main drivers for space weather disturbances.
- Both the scientific and the operational communities would benefit from the automatic recognition of their typical in-situ signature.
- Previous attempts only addressed the detection of a single type of events
- We propose a pipeline that returns, for streaming in-situ solar wind data, intervals that are likely to contain CIRs or ICMEs

Challenges

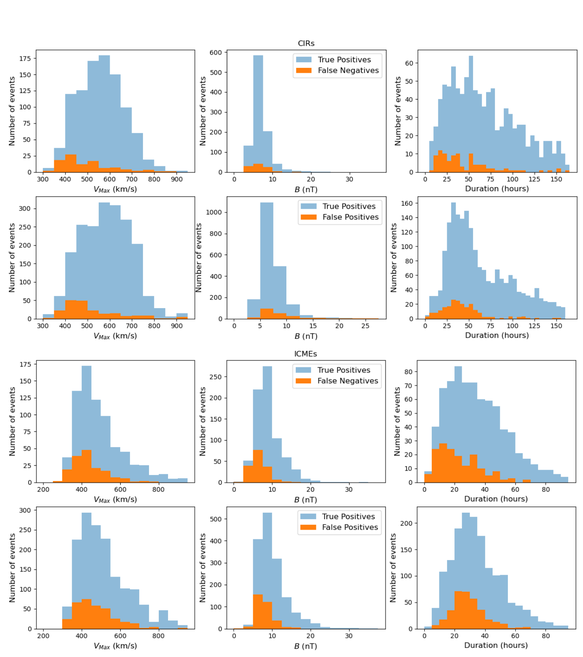
- Strong variability of the events signature including in the definition of their starting and ending times.
- Consecutive and overlapping events.
- Non-exhaustive event catalogs.

Detection performances



Precision-recall curves of our pipeline

	Max F1-score	
	ICMEs	CIRs
Our work	0,788	0,913
Rudisser et al. (2022)	0,75	0,75

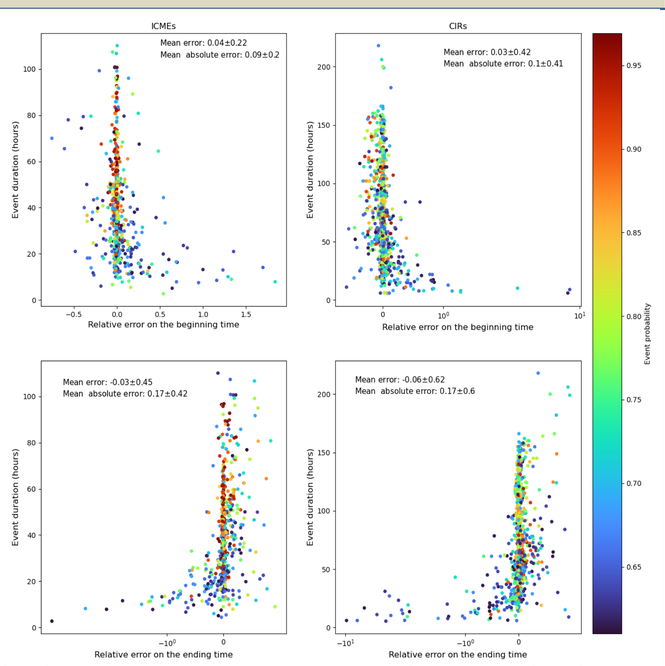


From left to right: distribution of the maximal velocity, IMF amplitude and duration of the pipeline true positives (blue), false negatives (orange, top) and false positives (orange, bottom) for both ICMEs and CIRs

- Detection errors mostly correspond to events with a « weak » signature

Errors made on the events starting and ending times

- Beginning predicted a little bit after their ground truth
- Endings predicted a little bit before their ground truth
- Highest errors are made on the smallest events

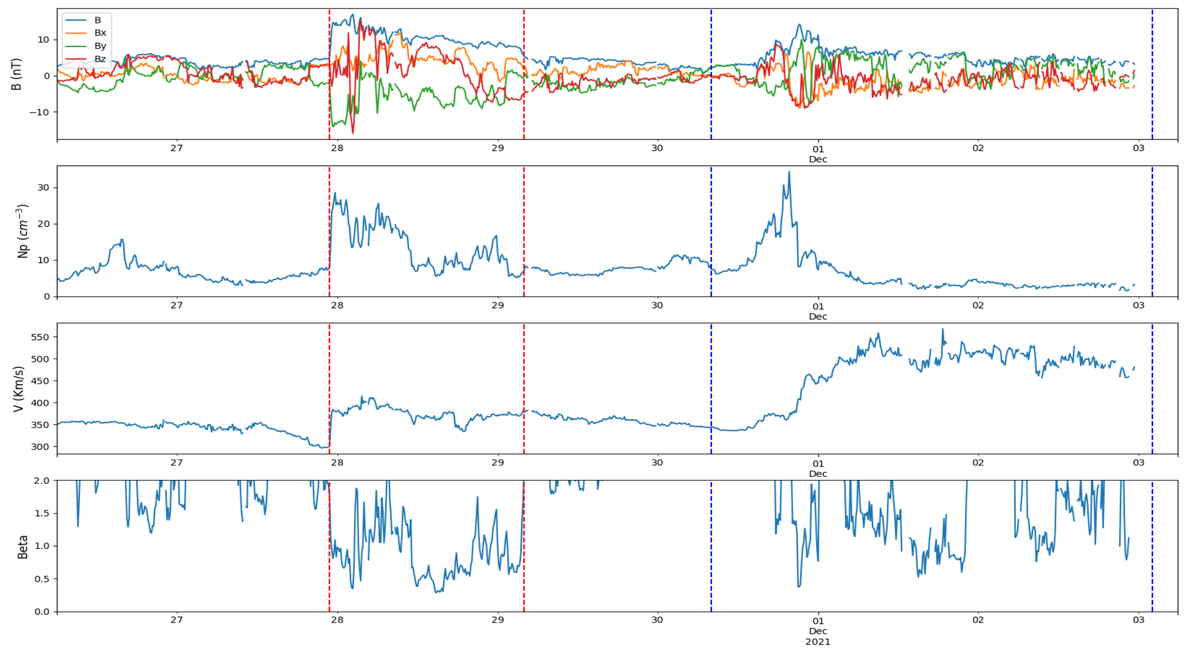


Distribution of the errors made on the starting and ending times of the catalog events along with their detection probability

	ICMEs				CIRs			
	Begin		end		begin		end	
	relative	absolute	relative	absolute	relative	absolute	relative	absolute
Our work	0,04±0,22	0,09±0,2	-0,03±0,45	0,17±0,42	0,03±0,42	0,1±0,41	-0,06±0,62	0,17±0,6
Rudisser et al. (2022)	-0,06±0,19	0,1±0,17	-0,01±0,25	0,15±0,22	-0,05±0,18	0,1±0,16	-0,07±0,22	0,12±0,2

Adapting object detection techniques to OMNI dataset

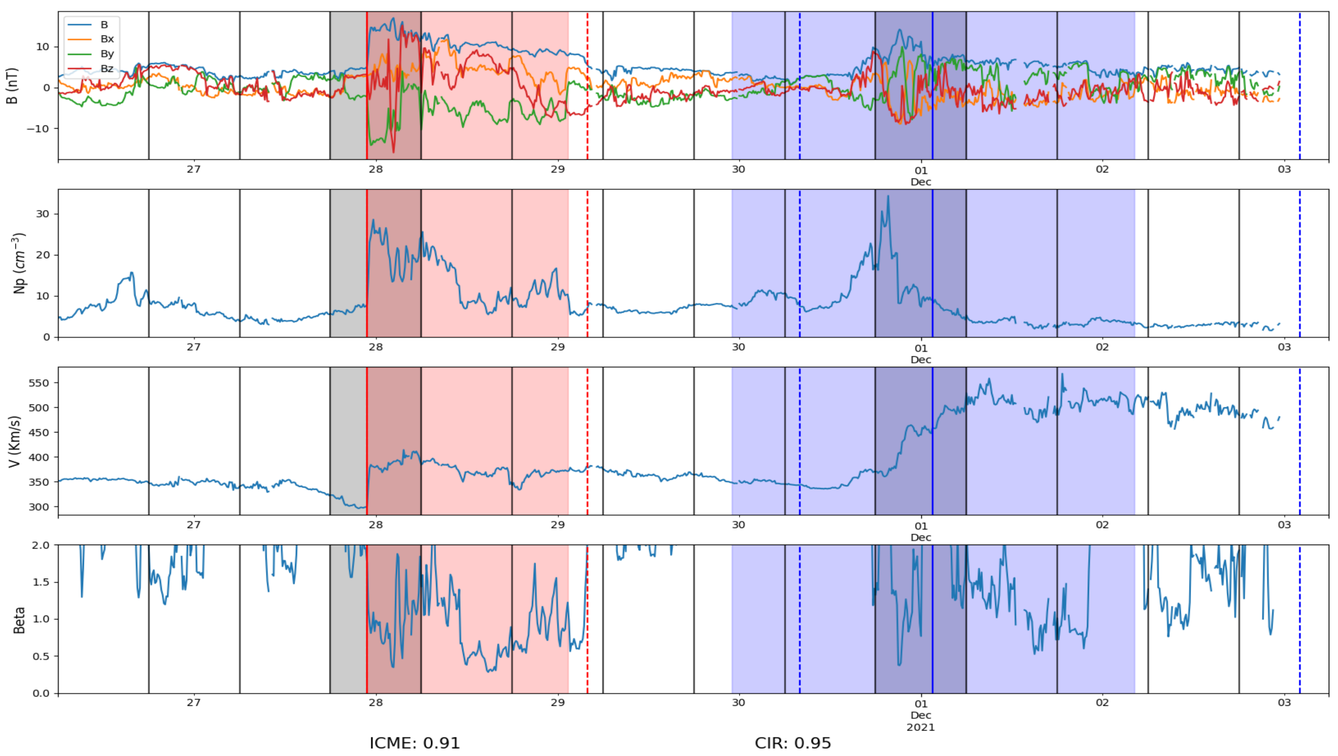
- OMNI dataset between 1995 and 2023
- Concatenation of the existing ICMEs (Nguyen et al. (2019), Chi et al. (2023), …) and CIRs (Grandin et al. (2019), Chi et al. (2018), …) catalogs



From top to bottom: OMNI measurement between July 19th, 2022 and July, 26th 2022 of the IMF, the solar wind proton density, bulk speed and plasma β. Target ICME (resp. CIR) are shown between the red (resp. blue) dashed lines

- Approach adapted from You Only Look Once (Redmon et al. (2015)
- Convolutional Neural Network (CNN) that predicts for each cell of a window of data:
  - Characteristic times t_{ij}
  - Possible event duration w_{ij}
  - Probability of belonging to a certain class j (ICME or CIR) p_{ij}
- Multi-terms Cost Function

$$\sum_{j=0}^{1}\sum_{i=1}^{N_{cells}} \lambda_t \delta_{ij}\left(t_{ij}-\tilde{t}_{ij}\right)^2 + \lambda_w \delta_{ij}\left(w_{ij}-\tilde{w}_{ij}\right)^2 + \lambda_{obj}\delta_{ij}\left(p_{ij}-\tilde{p}_{ij}\right)^2 + \lambda_{no\,obj}(1-\delta_{ij})\left(p_{ij}-\tilde{p}_{ij}\right)^2$$



Typical prediction made by our pipeline, the concerned cells are in grey and the red (resp. blue) intervals show the predicted ICME (resp. CIR).

Future work and perspectives

- Reduce the errors made on the event starting and ending times
- Use the prediction made to update the existing ICMEs and CIRs catalogs
- Adaptation to additional type of events or different datasets
- Interesting basis toward the early detection of event beginning
- Towards an ensemble model ?