Automatic Detection of ICMEs in Solar Wind Data

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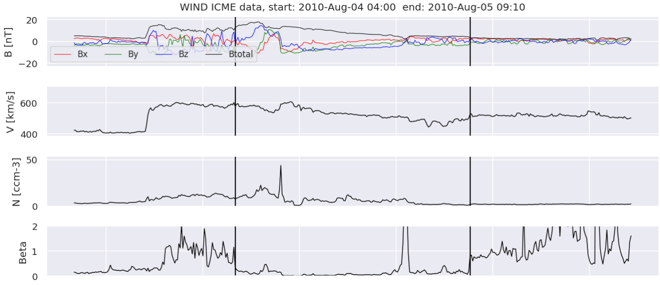
Abstract

Interplanetary coronal mass ejections (ICMEs) are one of the main drivers for space weather disturbances. In the past, different machine learning approaches have been used to automatically detect events in existing time series resulting from solar wind in situ data. However, classification, early detection and ultimately forecasting still remain challenges when facing the large amount of data from different instruments. We attempt to further enhance existing convolutional neural network (CNN) models through extending their possibilities to process data from multiple spacecraft. Additionally, we make an effort to extend the previously binary classification problem to a multiclass classification, to also include corotating interaction regions (CIRs) into the range of detectable phenomena. Ultimately, we aspire to explore the suitability of several other methods used in time series forecasting, in order to pave the way for the elaboration of an early warning system.

Introduction

Interplanetary coronal mass ejections (ICMEs) are one of the main drivers for space weather disturbances. In the past, different approaches have been used to automatically detect events in existing time series resulting from solar wind in situ data. However, accurate and fast detection still remains a challenge when facing the large amount of data from different instruments.



Example of an ICME captured by WIND

Introduction

Even though there are several criteria used for the identification of ICMEs, a simple threshold based method is not sufficient to reliably detect them in time series. Not all characteristics occur steadily and even experts disagree from time to time. Still, the huge amount of data calls for an automatic detection. Nguyen et al. (2019) proposed a machine learning approach using convolutional neural networks. Even though the results were quite reasonable and proved the general suitability of a machine learning algorithm to tackle the problem, it still left room for improvements.

We propose a pipeline using a UNet (Ronneberger et al. (2015)) including residual blocks, squeeze and excitation blocks, Atrous Spatial Pyramidal Pooling (ASPP) and attention blocks, similar to the ResUNet++ (Jha et al. (2019)), for the automatic detection of ICMEs. Comparing it to an existing method, we find that while achieving similar results, our model outperforms the baseline regarding GPU usage, training time and robustness to missing features, thus making it more usable for other datasets.

The method has been tested on in situ data from WIND. Additionally, it produced reasonable results on STEREO A and STEREO B datasets with less input parameters. The relatively fast training allows straightforward tuning of hyperparameters and could therefore easily be used to detect other structures and phenomena in solar wind data, such as corotating interaction regions.

Data and Catalogs

The 30 primary input variables

- bulk velocity and components (V, V_x , V_y , V_z)
- thermal velocity (V_{th})
- magnetic field, components and root mean square (B, B_x , B_y , B_z , σ_{B_x} , σ_{B_y}, σ_{B_z})
- density of protons and α particles, obtained from moment and nonlinear analysis (N_p, $N_{p,nl}$, $N_{a,nl}$)
- 15 canals of proton flux

were provided by the Magnetic Field Investigation (MFI), Solar Wind Experiment(SWE) and 3D Plasma and Energetic Particles Experiment (3DP) on board of the spacecraft WIND between 1997 October 1 and 2016 January 1. Three additional features were computed:

- plasma parameter β (ratio between thermal and magnetic pressure)
- dynamic pressure (P_{dyn})
- normalized magnetic fluctuations (σ_B)

Data and Catalogs

Additionally, we tested the pipeline on STEREO-A and STEREO-B data, which include less input parameters than the one used by Nguyen et al. (2019). These two datasets were complemented with a WIND dataset, reduced to the same input parameters:

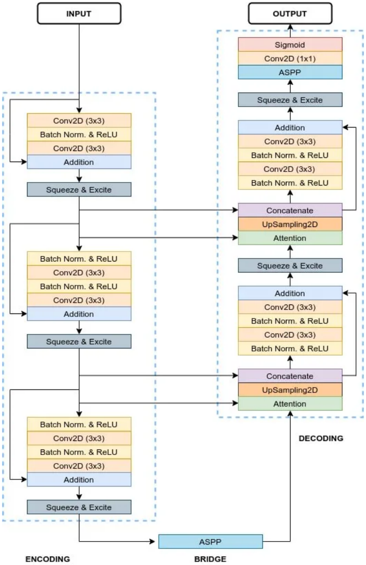
- bulk velocity (V)
- magnetic field and components (B, B_x , B_y , B_z)
- density of protons (N_p)
- proton temperature (T_p)

Three additional parameters were computed for these datasets as well:

- plasma parameter β
- dynamic pressure (P_{dyn})
- ratio between temperature and proton temperature (T_p/T_{ex})

We used the ICME catalog by Nguyen et al. 2019, which consists of several other ICME lists Jian et al., 2006, Lepping et al., 2006, Richardson and Cane, 2010, Chi et al., 2016, Nieves-Chinchilla et al., 2018 plus the ICMEs that were detected by the pipeline and thereupon added to the catalog. For the STEREO-A and STEREO-B datasets, as well as the reduced WIND dataset, we used the ICMECAT, an ICME catalog that was originally created during the HELCATS project Möstl et al., 2017 and updated in Möstl et al., 2020 to ICMECATv2.0. Guided by the criteria in Nieves-Chinchilla et al. 2018 it only contains events that show clear signatures of magnetic structure, called magnetic obstacles.

ResUNet++

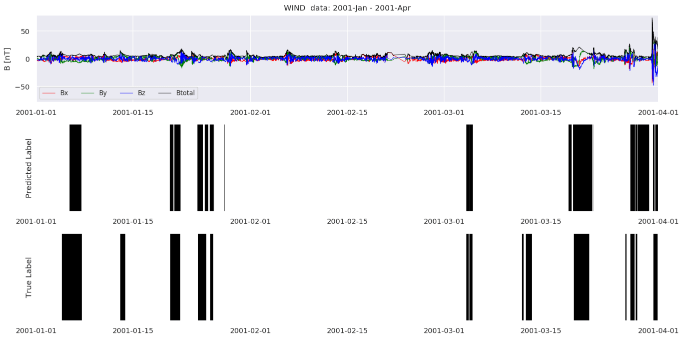


Our pipeline uses a sliding window approach to capture time frames and computes the additional features during preprocessing. Furthermore, we resample the data to a 10 minute resolution in order to get rid of holes in the datasets. The data is then scaled to have a mean value of 0 and a standard deviation of 1.

We compare each point in time to the eventlist and label it 1 if an ICME is occuring at the time, and 0 otherwise. Thereby we create a onedimensional segmentation map. For the network architecture we adapt the ResUNet++ Jha et al., 2019 to create an automatic event detection based on time series segmentation. During postprocessing, an eventlist is created out of the onedimensional segmentation map and compared to the ground truth for evaluation.

Results

Comparing the predicted label to the ground truth we find a mean PRAUC of 0.705 for the WIND dataset using all 33 input variables.



Comparison of predicted and true label between January 2001 and April 2001.

Outlook

Our proposed pipeline can be used for any time series segmentation problem. The straightforward implementation allows a simple extension to a multiclass classification problem and paves the way to include corotating interaction regions into the range of detectable phenomena within our pipeline. Furthermore, we hope to apply our model to similar problems in the future.
The results of our work will soon be submitted for publication. A tutorial on how to use our pipeline is available on github $(https : //github.com/epn - ml/Tutorial_I WF - ICMEs)$.

References

Yutian Chi, Chenglong Shen, Yuming Wang, Mengjiao Xu, Pinzhong Ye, and Shui Wang. Statistical Study of the Interplanetary Coronal Mass Ejections from 1995 to 2015. *Solar Physics*, 291(8):2419–2439, October 2016. doi: 10.1007/s11207-016-0971-5.

Debesh Jha, Pia H. Smedsrud, Michael A. Riegler, Dag Johansen, Thomas de Lange, Pal Halvorsen, and Havard D. Johansen. Resunet++: An advanced architecture for medical image segmentation, 2019.

L. Jian, C. T. Russell, J. G. Luhmann, and R. M. Skoug. Properties of Interplanetary Coronal Mass Ejections at One AU During 1995 2004. *Solar Physics*, 239(1-2):393–436, December 2006. doi: 10.1007/s11207-006-0133-2.

R. P. Lepping, D. B. Berdichevsky, C. C. Wu, A. Szabo, T. Narock, F. Mariani, A. J. Lazarus, and A. J. Quivers. A summary of WIND magnetic clouds for years 1995-2003: model-fitted parameters, associated errors and classifications. *Annales Geophysicae*, 24(1): 215–245, March 2006. doi: 10.5194/angeo-24-215-2006.

C. Möstl, A. Isavnin, P. D. Boakes, E. K. J. Kilpua, J. A. Davies, R. A. Harrison, D. Barnes, V. Krupar, J. P. Eastwood, S. W. Good, R. J. Forsyth, V. Bothmer, M. A. Reiss, T. Amerstorfer, R. M. Winslow, B. J. Anderson, L. C. Philpott, L. Rodriguez, A. P. Rouillard, P. Gallagher, T. Nieves-Chinchilla, and T. L. Zhang. Modeling observations of solar coronal mass ejections with heliospheric imagers verified with the heliophysics system observatory. *Space Weather*, 15(7):955–970, 2017.

Christian Möstl, Andreas J. Weiss, Rachel L. Bailey, Martin A. Reiss, Tanja Amerstorfer, Jürgen Hinterreiter, Maike Bauer, Scott W. McIntosh, Noé Lugaz, and David Stansby. Prediction of the In Situ Coronal Mass Ejection Rate for Solar Cycle 25: Implications for Parker Solar Probe In Situ Observations. *Astrophysical Journal*, 903(2):92, November 2020. doi: 10.3847/1538-4357/abb9a1.

Gautier Nguyen, Nicolas Aunai, Dominique Fontaine, Erwan Le Pennec, Joris Van den Bossche, Alexis Jeandet, Brice Bakkali, Louis Vignoli, and Bruno Regaldo-Saint Blancard. Automatic Detection of Interplanetary Coronal Mass Ejections from In Situ Data: A Deep Learning Approach. *Astrophysical Journal*, 874(2):145, April 2019. doi: 10.3847/1538-4357/ab0d24.

T. Nieves-Chinchilla, A. Vourlidas, J. C. Raymond, M. G. Linton, N. Al-haddad, N. P. Savani, A. Szabo, and M. A. Hidalgo. Understanding the Internal Magnetic Field Configurations of ICMEs Using More than 20 Years of Wind Observations. *Solar Physics*, 293(2):25, February 2018. doi: 10.1007/s11207-018-1247-z.

I. G. Richardson and H. V. Cane. Near-Earth Interplanetary Coronal Mass Ejections During Solar Cycle 23 (1996 - 2009): Catalog and Summary of Properties. *Solar Physics*, 264(1):189–237, June 2010. doi: 10.1007/s11207-010-9568-6.

Europlanet 2024 RI has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 871149.

A. Windisch acknowledges support by the U.S. Department of Energy, Office of Science, Office of Nuclear Physics under Award Number # DE-FG-02-05ER41375.

T. Amerstorfer thanks the Austrian Science Fund (FWF): P31265-N27

C. Möstl and R. Bailey thank the Austrian Science Fund (FWF): P31659-N27.