AUSTRIA'S LEADING RESEARCH CENTER
FOR DATA-DRIVEN BUSINESS AND BIG DATA ANALYTICS

Automatic Detection and Classification of ICMEs in Solar Wind Data

H. Rüdisser[1,2], A. Windisch[1,4], U.V. Amerstorfer[3], T. Amerstorfer[3], C. Möstl[3], R.L. Bailey[5]

[1]Know Center, Graz, Austria; [2]University of Graz, Graz, Austria;

[3]Space Research Institute, Austrian Academy of Sciences, Graz, Austria;

[4]Department of Physics, Washington University in St. Louis, MO 63130, USA;

[5]Conrad Observatory, ZAMG, Vienna, Austria

Abstract

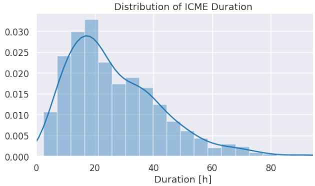
Interplanetary coronal mass ejections (ICMEs) are one of the main drivers for space weather disturbances. In the past, different machine learning approaches have been used to automatically detect events in existing time series resulting from solar wind in situ data. However, classification, early detection 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.

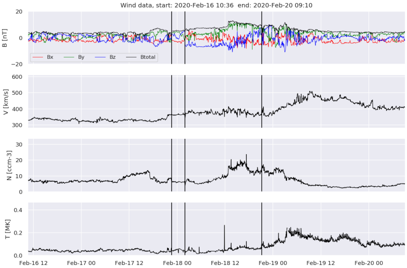
Introduction

The Classification Problem

The first step on the way to an early warning system is the reliable detection of ICMEs in an existing time series. While CNNs are often used to discover objects or patterns in images or data series, there are two main problems when facing our specific task:

- Duration variability
- Rather ambiguous definition of start and end



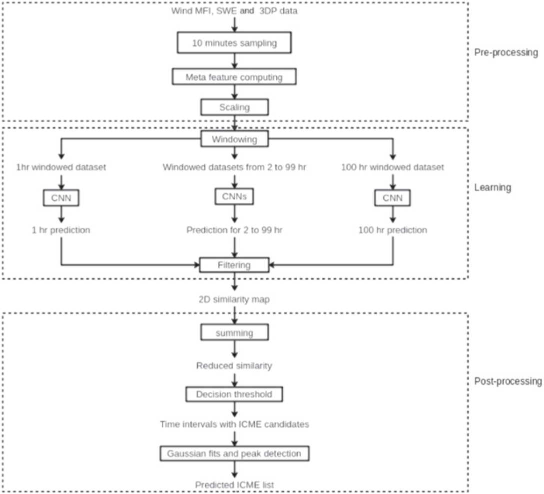


Distribution of ICME Duration and an example event, showing start and end of the ICME and start of the magnetic obstacle

Model 1

Architecture and Pipeline

Nguyen et al. 2019 proposed a deep learning approach consisting of several CNNs which were trained to predict a similarity parameter. At pre-processing, the model takes 33 input variables from in-situ solar wind data, performs resampling and scaling and computes additional features. This method reasonably overcomes the problem of having highly varying durations in the range of ICMEs by ultimately combining the output of 100 separate CNNs which have been trained on different time lengths. A post-processing step based on peak detection is then used to convert the 2D similarity map to a list of predicted ICMEs.

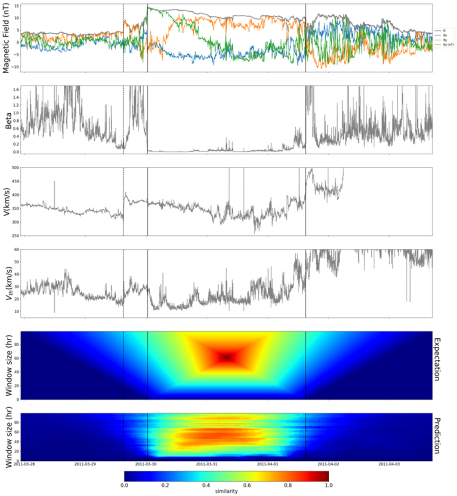


Pipeline of Model 1, divided into pre-processing, learning and post-processing (Nguyen et al. [2019])

Model 1

Performance

The model had previously been tested on WIND data and achieved a maximum recall of 84% ± 4.5% and a maximum precision of 84% ± 2.6%. The robustness to missing features could be established, even though the performance thus lacked in accuracy.

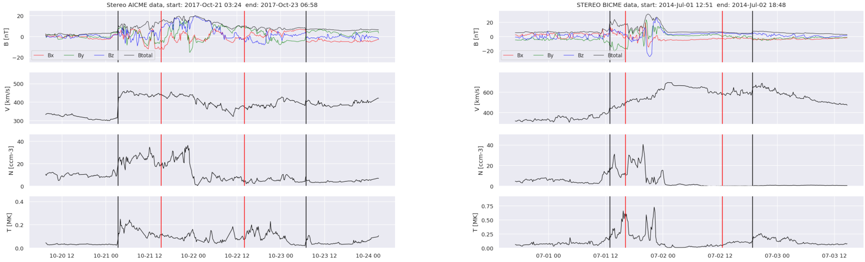


Observation during ICME from WIND spacecraft. Solid vertical lines delimitate the ICME. Dashed vertical line indicates beginning of sheath. From top to bottom are representations of magnetic field amplitude and components, plasma parameter, solar wind velocity, thermal velocity, similarity the ICMEs have with sliding windows of size 1 to 100, similarity predicted by Model 1. (Nguyen et al. [2019])

Model 1

Reimplementation

We reimplemented the pipeline and additionally tested it on STEREO A and STEREO B data, which contain less variables than WIND data. The model was still able to achieve similar recall on all three data sets but the precision went down to around 30 %.
However, keeping in mind the ultimate goal, early recognition is an extremely important feature. The preciseness achieved by the model when delivering start and end time is limited, probably due to the fact, that the post-processing is mainly based on arbitrary thresholds.



Events from STEREO A (left) and STEREO B (right). Black vertical lines delimitate true event, red vertical lines delimitate predicted event.

Model 1

Thoughts

Even though Model 1 performs reasonably well in terms of detection rate, we still observed some critical features.

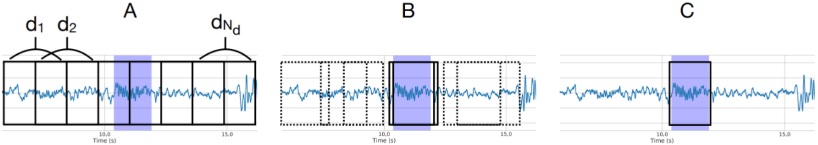
- Training 100 different models is computationally expensive and takes around 55h with GPU support
- Start and endtime could not be precisely predicted

Another interesting result is the fact, that simultaneously training the model on WIND, STEREO A and STEREO B data did not improve the performance as expected. As a matter of fact, the resulting model was not able to reliably detect events at all. This is a clear indicator, that the three data sets in fact are very different from each other and enormously raise the level of variability in events.

Model 2

Architecture and Pipeline

A comparable problem is the detection of sleep related micro-architecture events in EEG series, for which Chambon et al. 2018 proposed a similar approach. The Dreem One Shot Event Detector (DOSED) is inspired by object detectors developed for computer vision and likewise works with a convolutional neural network. The raw data is used to build a feature representation and localization and classification are performed by two separate modules. Even though the problem in general is much easier due to less variability in how events present themselves, the model has substantial advantages in the post - processing step.



Prediction procedure for DOSED. A: N_d default events d_i are generated over the EEG sample. B: network predicts potential events (adjusted centers and durations, potential event labels). C: non-maximum suppression. network returns centers, durations and labels of events (Chambon et al. [2018])

Conclusion

Model 1

- Reasonably overcomes the problem of different durations
- Lacks preciseness in giving start and endtime
- Training takes around 55 h

Model 2

- Proposes a more advanced post - processing step
- Short training time
- Only uses one window size, therefore not yet able to reliably detect ICMEs

Through combining the presented models in order to overcome their specific weaknesses, we hope to further improve detection rate and accuracy for providing start and endtime independent from the data source or specific event.

References

Stanislas Chambon, Valentin Thorey, Pierrick J. Arnal, Emmanuel Mignot, and Alexandre Gramfort. *A deep learning architecture to detect events in EEG signals during sleep*. IEEE 28th International Workshop on Machine Learning for Signal Processing (MLSP), 2018, 2018.

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*. The Astrophysical Journal, Vol. 874, No. 2, April 2019, 2019.

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.