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Automatic Detection of ICMEs in Solar Wind Data

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Abstract

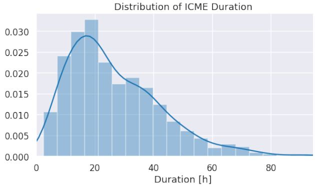
Interplanetary coronal mass ejections (ICMEs) are one of the main drivers for space weather disturbances. In the past, different machine learning approaches have been used to automatically detect events in existing time series resulting from solar wind in situ data. However, classification, early detection and ultimately forecasting still remain challenges when facing the large amount of data from different instruments. We propose the utilisation of an adaption of the ResUNet++, which was originally used for medical image segmentation. Even though additional cross validation is needed, our model seems to achieve similar maximum recall and precision and outperform the baseline in terms of GPU usage and mean average precision. Its relatively fast training facilitates the tuning of hyperparameters and thereby allows straightforward application of the pipeline for similar problems. Ultimately, we aspire to extend the previously binary classification problem to a multiclass classification, to also include Corotating Interaction Regions (CIRs) into the range of detectable phenomena.

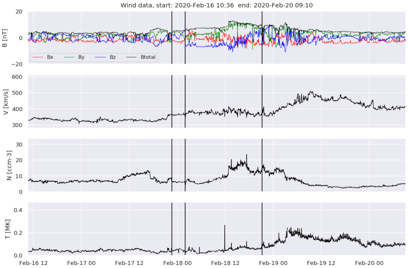
Introduction

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

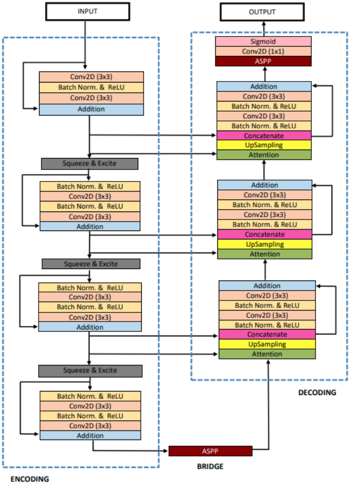
ResUNet++

Architecture

Jha et al. 2019 proposed an advanced architecture for medical image segmentation based on the Deep Residual Unet (Zhang and Liu 2017), including residual blocks, squeeze and excitation blocks, ASPP and attention blocks.

The model outperforms other state of the art methods and is able to learn complex features in images to predict masks.

We adapted the architecture for our use case and use a sliding window approach to detect ICME events and non-events in time series.



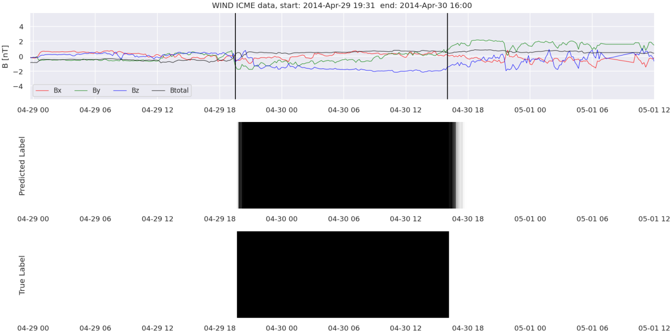
Block diagram of the proposed ResUNet++ architecture. (Jha et al. [2019])

ResUNet++

Pipeline

At pre-processing, the model performs resampling and scaling on in-situ solar wind data, computes additional features and ultimately takes 33 input variables. A sliding window approach is used to generate instances covering approximately one week in time. This method reasonably overcomes the problem of having highly varying durations in the range of ICMEs by choosing a time window, that covers even the longest durations.

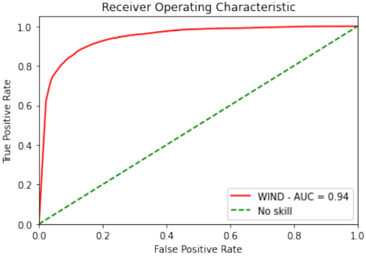
The ResUNet++ predicts a value between 0 and 1, which needs a threshold based post-processing. Ultimately, we convert the labels to a list of predicted ICMEs.

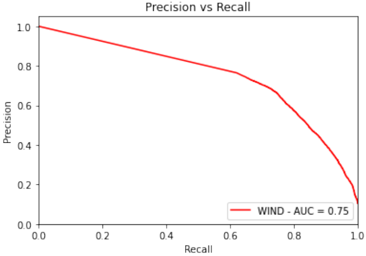


Magnetic field components of an example event together with predicted and true label

Results

Comparing the list of predicted ICMEs to the list of true ICMEs, we find a precision of 60.9% and a recall of 83.1%. Since this evaluation method is highly dependent on the threshold for the percentage of the predicted ICMEs which need to overlap with the true ICME in order to count as a detected event, we additionally compare the predicted label for each individual timestep to the true label.





True positive rate over false positive rate for each point in time and its area under the curve, compared to random guessing (left), Precision over Recall for each point in time and its area under the curve (right)

Conclusion

- We propose a fast and efficient method for the automatic detection of ICMEs
- Additional tuning of hyperparameters and cross validation is needed
- The next steps will be to thoroughly test the pipeline on other datasets, such as STEREO A and STEREO B

References

D. Jha, P. H. Smedsrud, M. A. Riegler, D. Johansen, T. D. Lange, P. Halvorsen, and H. D. Johansen. Resunet++: An advanced architecture for medical image segmentation. In *2019 IEEE International Symposium on Multimedia (ISM)*, pages 225–230, 2019.

Zhengxin Zhang and Qingjie Liu. Road extraction by deep residual u-net. *IEEE Geoscience and Remote Sensing Letters*, PP, 11 2017. doi: 10.1109/LGRS.2018.2802944.

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