Automatic Detection of Interplanetary Coronal Mass Ejections

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Interplanetary Coronal Mass Ejections

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.

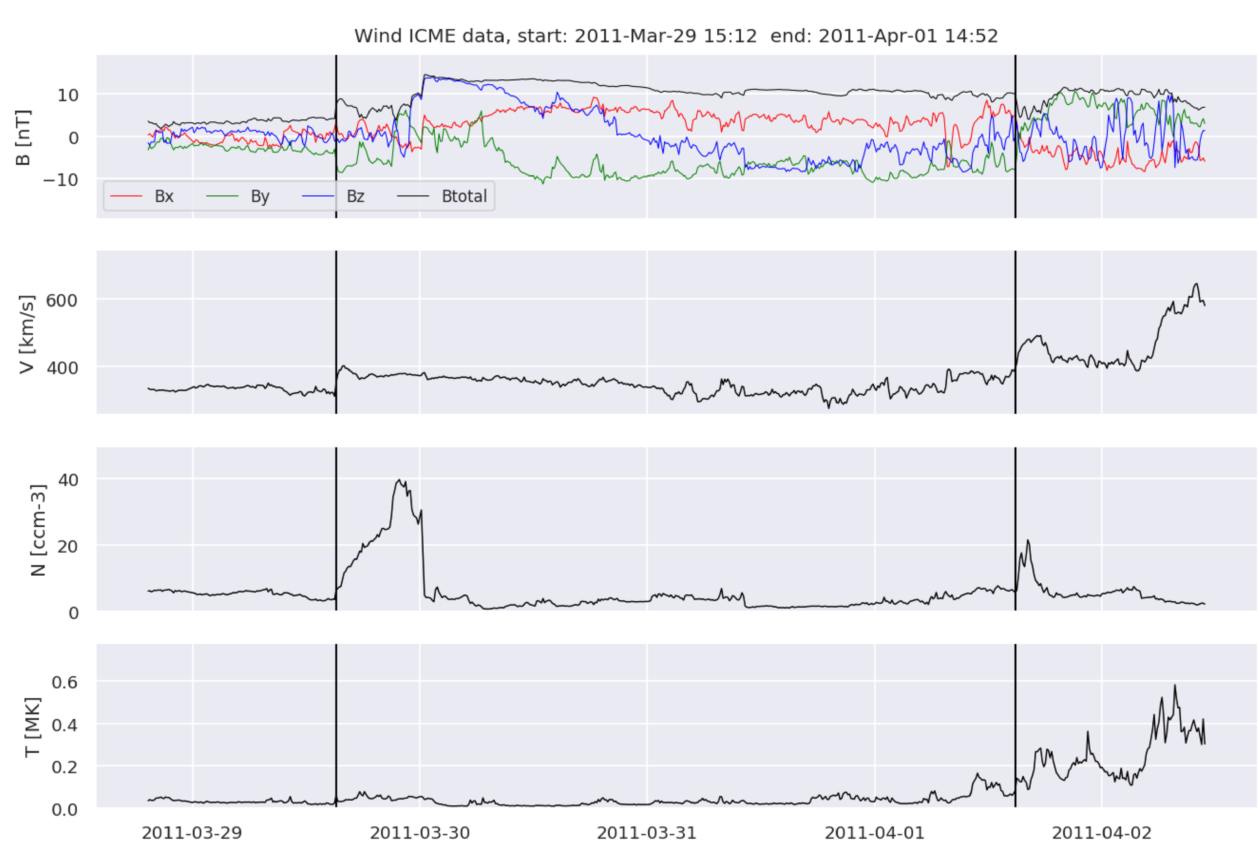

Fig. 1: Solar wind in situ data from the Wind spacecraft located at the Lagrangian Point L1, showing an ICME. The solid vertical lines delimitate the event, including shock, sheath and magnetic cloud. From top to bottom: magnetic field amplitude and components, solar wind velocity, proton density, proton temperature.

Figure 1 depicts an example event exhibiting the typical signatures of an ICME featuring a magnetic cloud (MC), notwithstanding the existence of events without the presence of aforementioned structure. The top panel shows a smooth rotation of the magnetic field components and an enhanced total magnetic field compared to the surrounding ambient solar wind. The second panel shows a first enhanced, but then monotonically declining velocity profile compared to the preceding solar wind. Both the velocity and the magnetic field exhibit a sudden sharp jump, the so called shock, which is followed by the sheath, a turbulent region preceding the magnetic could. The third panel depicts an extreme proton density decrease after the proton density increase during the shock and sheath, and the fourth panel shows a reduced proton temperature [4, 1, 8].

Automatic Detection

The circumstance that not all ICMEs even exhibit standard features and there exists no feature present in all ICMEs, hinders a standardized identification method and fuels the need for time consuming visual expert labeling. Nevertheless, this visual inspection is highly biased, emphasised through the existence of several catalogs only partially overlapping with each other [11, 7, 9, 12, 10]. Furthermore, ranging from a few hours to multiple days, the duration of the events shows a high variability.

ResUNet++

[11] explained the need for a machine learning solution and proposed a pipeline based on the prediction of a similarity parameter of sliding windows of 100 different sizes. We restated the problem as a time series segmentation task and proposed a variation of a ResUNet++, which is an improved ResUNet architecture for colonoscopic image segmentation and significantly outperforms other state of the art algorithms used for semantic segmentation. The typical ResUNet architecture is extended through the application of squeeze-and-excitation units [6], atrous spatial pyramidal pooling [5, 3, 2] and attention units [13], thus enhancing the focus on relevant features and areas, increasing generalization, reducing computational cost and capturing channel-wise dependencies. A block diagram of the used model architecture is shown in Figure 2.

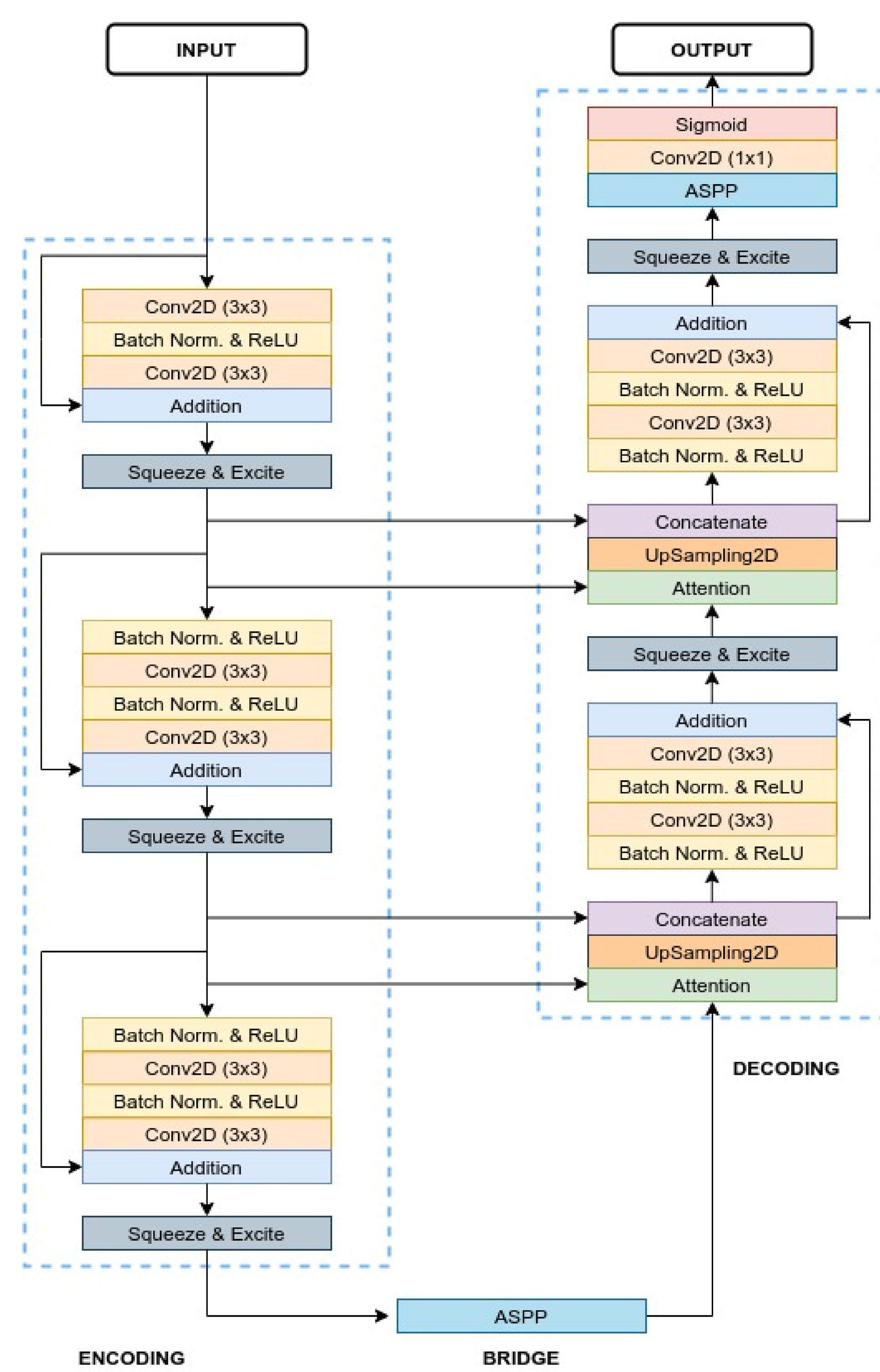

Fig. 2: Block diagram of the model architecture.

We find that while achieving similar results, our model outperforms the baseline regarding training time, thus making it more usable for other datasets.

Result & Outlook

The method has been tested on in situ data from Wind between 1997 and 2015 with a Dice Coefficient of 0.71. Additionally, it produced reasonable results on datasets with less input parameters and smaller training sets from Wind, STEREO-A and STEREO-B with Dice Coefficients of 0.56, 0.58 and 0.63. 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.

Acknowledgements

H.T.R., A.W., and U.V.A. thank Europlanet 2024 RI. Europlanet 2024 RI has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 871149.

References

[1] L. Burlaga et al. "Magnetic loop behind an interplanetary shock: Voyager, Helios, and IMP 8 observations". In: 86.A8 (Aug. 1981), pp. 6673–6684. DOI: 10.1029/JA086iA08p06673.

[2] Liang-Chieh Chen et al. "DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 40.4 (2018), pp. 834–848. DOI: 10.1109/TPAMI.2017.2699184.

[3] Liang-Chieh Chen et al. *Rethinking Atrous Convolution for Semantic Image Segmentation.* 2017. arXiv: 1706.05587 [cs.CV].

[4] J. T. Gosling, V. Pizzo, and S. J. Bame. "Anomalously low proton temperatures in the solar wind following interplanetary shock waves—evidence for magnetic bottles?" In: 78.13 (Jan. 1973), p. 2001. DOI: 10.1029/JA078i013p02001.

[5] Kaiming He et al. "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". In: *Lecture Notes in Computer Science* (2014), pp. 346–361. ISSN: 1611-3349. DOI: 10.1007/978-3-319-10578-9_23. URL: http://dx.doi.org/10.1007/978-3-319-10578-9_23.

[6] Jie Hu et al. *Squeeze-and-Excitation Networks.* 2019. arXiv: 1709.01507 [cs.CV].

[7] L. Jian et al. "Properties of Interplanetary Coronal Mass Ejections at One AU During 1995 2004". In: 239.1-2 (Dec. 2006), pp. 393–436. DOI: 10.1007/s11207-006-0133-2.

[8] L. W. Klein and L. F. Burlaga. "Interplanetary magnetic clouds at 1 AU". In: 87.A2 (Feb. 1982), pp. 613–624. DOI: 10.1029/JA087iA02p00613.

[9] R. P. Lepping et al. "A summary of WIND magnetic clouds for years 1995-2003: model-fitted parameters, associated errors and classifications". In: *Annales Geophysicae* 24.1 (Mar. 2006), pp. 215–245. DOI: 10.5194/angeo-24-215-2006.

[10] Christian Möstl et al. "Prediction of the In Situ Coronal Mass Ejection Rate for Solar Cycle 25: Implications for Parker Solar Probe In Situ Observations". In: 903.2, 92 (Nov. 2020), p. 92. DOI: 10.3847/1538-4357/abb9a1. arXiv: 2007.14743 [astro-ph.SR].

[11] Gautier Nguyen et al. "Automatic Detection of Interplanetary Coronal Mass Ejections from In Situ Data: A Deep Learning Approach". In: 874.2, 145 (Apr. 2019), p. 145. DOI: 10.3847/1538-4357/ab0d24. arXiv: 1903.10780 [astro-ph.SR].

[12] T. Nieves-Chinchilla et al. "Understanding the Internal Magnetic Field Configurations of ICMEs Using More than 20 Years of Wind Observations". In: 293.2, 25 (Feb. 2018), p. 25. DOI: 10.1007/s11207-018-1247-z.

[13] Ashish Vaswani et al. *Attention Is All You Need.* 2017. arXiv: 1706.03762 [cs.CL].