

## How Machine Learning can assist Data Analysis of Ground Based Radio Astronomy

Stefan Wagner (1), Valentin N. Melnik (2) and Helmut O. Rucker (1)

(1) Commission for Astronomy, Austrian Academy of Sciences, Graz, Austria, (2) Institute of Radio Astronomy, NASU, Kharkiv, Ukraine, (Stefan.Wagner@oeaw.ac.at)

### Abstract

Type III bursts are intense, non-thermal sporadic solar radio emissions and can be characterized by their rapid development in time and frequency in the dynamic spectrum. Produced by accelerated electron beams which propagate along open magnetic field lines during the impulsive phase of a flare via the plasma emission mechanism and generated at the local electron plasma frequency  $f_p \simeq 9\sqrt{n_e}$  kHz ( $n_e$  as the plasma density: number of electrons per volume  $\text{cm}^{-3}$  [1]) (the fundamental  $F$  component) and/or its harmonic  $2f_p$  (the harmonic  $H$  component), their frequency ranges from  $\sim 1$  GHz to  $\sim 20$  kHz thus making them observable by ground and space-borne radio telescopes respectively. Beside a fast drift from high to low frequencies, bursts duration increases simultaneously as the drift rate decreases at lower frequencies. These strong relations between features and type III bursts are very distinct to other bursts that are accompanying the periods of solar activities and represent an excellent candidate for pattern recognition by supervised machine learning. Convolutional Neural Networks (CNNs) enjoy a great success in large scale image and video recognition [2], [3], [4] and will be used in the present work to scan as a sliding window along the time axis over a dynamic spectrum, returning a time-series like classification probability for type III radio bursts. For later analysis, the classified bursts are collected in burst-probability, burst-duration and max. burst-intensity bins. Initially, the presented network was trained and tested [5] on High Frequency Receiver data from the space-borne observatory STEREO/WAVES covering a frequency range from 125 to 16025 kHz [6]. For large scale data analysis, the model was applied on ground based measurements from UTR-2 and URAN-2, covering a frequency range from 8 to 32 MHz [7] as well. By re-training the network with extended one-hot encoded training data [8], the model will classify additional ra-

dio features hence extending its range of use in modern radio astronomy.

### Acknowledgements

We would like to thank **Patrick Kasper** (3) for the great support in computer sciences and the **ÖAW - Austrian Academy of Sciences** and the **Dr. Anton Oelzelt-Newin foundation** making the project possible.

(3) Institute of Interactive Systems and Data Science, Technical University, Graz, Austria

### References

- [1] Krupar V. et al.: Statistical Survey of Type III Radio Bursts at Long Wavelengths Observed by the Solar TERrestrial RELations Observatory (STEREO)/Waves Instruments: Goniopolarimetric Properties and Radio Source Locations, *Solar Physics*, Vol. 289, pp. 4633-4652, 2014.
- [2] Zeiler M. and Fergus R.: Visualizing and understanding convolutional networks, *CoRR*, Vol. abs/1311.2901, 2013.
- [3] Sermanet P. et al.: OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks, *CoRR*, Vol. abs/1312.6229, 2014.
- [4] Szegedy C., et al.: Going deeper with convolutions, *CoRR*, Vol. abs/1409.4842, 2014.
- [5] Wagner S., Panchenko M. and Rucker H. O.: Solar Radio Bursts Pattern Recognition by Supervised Machine Learning, *Geophysical Research Abstracts*, Vol. 21, EGU2019-4470, 2019.
- [6] Bougeret J.L. et al.: S/WAVES: The radio and plasma wave investigation on the STEREO mission, *Space Science Reviews*, Vol. 136, pp. 487-528, 2008.
- [7] Konovalenko A. et al.: The modern radio astronomy network in Ukraine: UTR-2, URAN and GURT, *Experimental Astronomy*, Vol. 42, pp. 11-48 2016.
- [8] Beck J. E. and Woolf B. P.: High-Level Student Modeling with Machine Learning, *ITS 2000: Intelligent Tutoring Systems*, pp. 584-593, Springer, 2000.