Deep learning for RFI mitigation of Nançay data and its impact on pulsar timing

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Pulsars are fast-rotating and highly-magnetized stars producing beams of radio emission at their magnetic poles. Because the magnetic axis is not aligned with the spin axis, the beams are swept across the sky during the rotation of the star, thus creating periodic pulses to remote observers. To study pulsars, we record Times of Arrival (TOAs) [1] of periodic radio pulses at a telescope, and use the TOAs to estimate the parameters of the pulsar and its environment with high precision. However, radio observations of pulsars are impacted by different perturbating signals called radio frequency interferences (RFIs), which result from human activities such as telecommunications. These interferences need to be removed from observations to achieve the most precise pulsar timing.

In this contribution we present our method to perform RFI excision from pulsar observations using a deep learning "DL" algorithm. The architecture is based on U-net [2], a convolutional neural network to detect RFIs in the dynamic spectrograms of the observations and generate a binary mask. The dataset comprises 45 000 real observations from the Nançay Radio Telescope (France) between 1.2GHz and 3.5GHz, and for the training process we include masks generated by the Coast Guard [3] standard statistical method as the ground truth value. We tested four configurations during the learning process, including weighted classes and adding simulated RFIs to our datasets to select the method with minimal false-negative detections. We apply the best configuration to remove RFIs on 9 specific pulsars, 6 fast rotating pulsars (millisecond period) and 3 slower ones, and assess the performance of our method against Coast Guard. TOA uncertainties as well as signal-to-noise ratios (SNRs) are obtained with both methods and are compared for each cleaned observation.

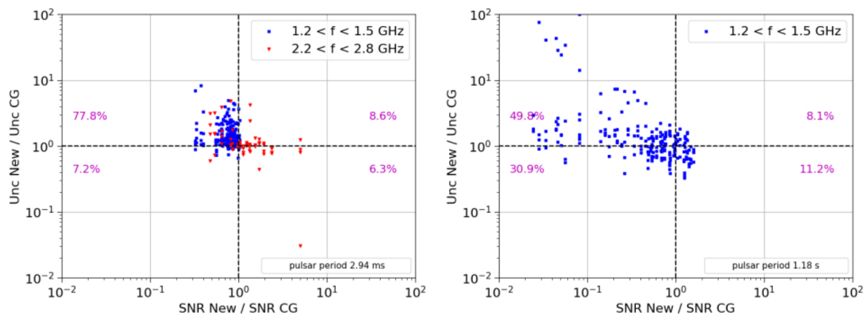

Figure 1. TOA uncertainties and SNRs for a fast (left panel) and a slow (right panel) pulsar. For improved TOAs uncertainties, points should be in the lower half of the plot, and for improved signal-to-noise ratio it should be on the right half.

In the cleaned observations with the DL method, SNR is better in 6% of the cases, and between 7-40% of the TOAs have smaller uncertainties. Using Coast Guard masks as the ground truth value may include a bias, since the deep learning method can only perform as well as the standard method, as we do in many cases (Fig. 1). We conclude that some RFIs remain in the observations cleaned by the DL method, especially short duration periodic interferences.

References

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[3] P. Lazarus, R. Karuppusamy, E. Graikou, R. N. Caballero, D. J. Champion, K. J. Lee, J. P. W. Verbiest, and M. Kramer, "Prospects for high-precision pulsar timing with the new Effelsberg PSRIX backend", *MNRAS*, **458**, 2016.