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Using deep learning to detect radio frequency interference in pulsar observations

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Abstract

Pulsars are highly-magnetized, rapidly-rotating neutron stars producing beams of radio emission that are swept across the sky as pulsars about their axis, in a similar way as lighthouses. Radio observations of pulsars are unfortunately subjected to numerous types of parasite signals, the so-called "Radio Frequency Interferences" (RFIs). RFIs result from human activity and need to be excised in order to be able to study pulsars with the cleanest possible data. The RFI excision method we present here detects RFIs in dynamic spectograms of the radio pulsar observations, using a deep neural network. Dynamic spectrograms are treated as images by the network, which in turn uses image segmentation to classify the points in the time-frequency space as RFI or non-RFI data. Preliminary results indicate that the network can detect most RFI types while being less "destructive", i.e., it discards less actual pulsar signal than common RFI excision methods based on statistical thresholding.

1 Introduction

Neutron star are compact objects that result from supernova explosions of massive stars at the end of their lives. Some of them produce radio beams above their magnetic poles, that are swept across the sky as the neutron star rotates. These so-called "pulsars" thereby produce radio emission modulated at the rotational period, with periodicities ranging from a few milliseconds for the fastest-rotating pulsars to several tens of seconds. Pulsar observations find their applications in a wide range of Physics and Astrophysics domains, such as the study of the equation of state in extreme conditions of density and temperature, plasma physics, gravitational wave searches or tests of Gravity theories.

Radio pulsars can be observed with large radio telescopes such as the Nançay Radio Telescope (NRT), a 94-m equivalent meridian telescope located near Orléans, France. Radio observations with the NRT and with other similar instruments are subjected to parasite signals, the so-called RFIs, originating from satellite transmission, telecommunications, and human activity in general. Identification and separation of noise from signal of interest is a classical application of deep neural network techniques [1, 2]. Rejecting parasite signals is key for studying pulsars in radio, since the latter objects are in most cases much fainter than RFI signals. Image segmentation, which consists in classifying pixels from a given image, is widely used for the detection of objects in pictures or for motion detection problems. By considering NRT observations as an ensemble of time-frequency domain images (i.e. dynamic spectrograms), the usage of image segmentation techniques can provide an alternative to current statistical methods.

2 Observational data

In this work we use observational data taken with the Nançay Radio Telescope, at frequencies ranging from $\sim$1.4 GHz to 3.5 GHz. Data are recorded in the form of hypercubes that contain pulsar pulse profiles (i.e. radio intensity as a function of the pulsar's rotational phase) as a function of time and frequency. Each observation with the "NUPPI" backend currently in use for pulsar observations with the NRT comprises 128 frequency channels of 4 MHz (the total bandwidth of the observations is therefore 512 MHz) and varying numbers of time sub-integrations. Roughly speaking, the length of these sub-integrations depends on the observed pulsar's rotational period, with shorter (and thus more numerous) time sub-integrations being used for the fastest-rotating objects. In addition to these hypercubes we also make use of "data masks" that are produced using Coast Guard [3], a commonly-used tool for identifying RFI in pulsar data that relies on statistical thresholding. The masks consist in binary matrices of dimension (nchan, nsub) (with nchan the number of frequency channels in a given observation and nsub the number of time sub-integrations) indicating which channels and sub-integrations were flagged as RFI by Coast Guard.

2.1 The neural network

RFI identification in the time-frequency domain is equivalent to pixel classification with two different classes: RFI and non-RFI. Before actually conducting the classification, also known as image segmentation, we make use of a Convolutional Neural Network (CNN) that enables the extraction of discriminating features of the different classes [4]. The network follows the U-net architecture [5], in which

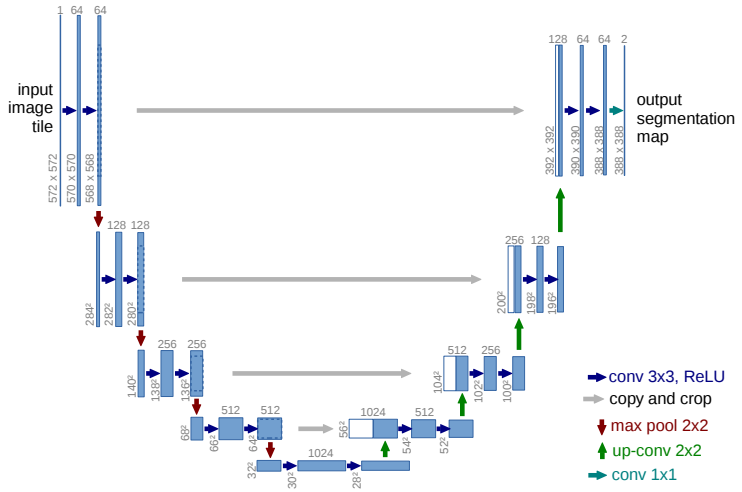

Figure 1. The U-net architecture. Figure adapted from [5], see this article for the details.

the descending part determines the discriminating features through convolutions and stores them into vectors. The ascending part then generates masks from the vectors via transposed convolutions. The two different parts of the network are connected by concatenation, as illustrated in Figure 1. The dimensions of the masks generated in the process only depend on the input data, which enables the analysis of observations with varying sizes.

Network training is supervised, and the optimized cost function is the mean Jaccard index, which represents the overlap between the predicted and the true masks, the latter being used as input for the training.

2.2 The training dataset

The dataset used for training the neural network consists in the NRT radio observations of pulsars made until now, and the masks associated with each observation as generated with Coast Guard. These masks serve as "targets" for the network training. Radio observations are reduced by determining the median of the total intensity curve in each channel and sub-integration. The entire spectral and time information is therefore preserved in the spectrograms, which are used for identifying RFI. Our dataset comprises 35354 observations, 80% of which were made at the central frequency of 1.4 GHz and 66% of which being observations of millisecond pulsars, i.e., the fastest-rotating objects. The training, validation and test datasets respectively comprise 50, 30, and 20% of all the available observations and masks.

3 Preliminary results

Although very preliminary, current results are promising but they also indicate that the network does not manage to flag certain types of RFI signals affecting the baseline of the pulsar pulse profiles, whereas Coast Guard manages to clean up profile baselines more efficiently. However, the masks generated by the neural network are less "destructive" than their Coast Guard counterparts: they flag smaller fractions of the datasets as RFI pixels, while leading to cleaned pulse profiles that have similar signal-to-noise ratios. Figure 2 shows masks generated with Coast Guard and with our neural network, for a 1.4 GHz observation of the millisecond pulsar J1909−3744. As can be seen from the Figure, we find significant overlap between the channels and indices flagged by the two methods, but the results are not identical and in this case our neural network appears to be slightly less destructive. The signal-to-noise ratios of the total profiles for the same observation of J1909−3744 are close to identical in this case, which is encouraging given how preliminary the results are.

Our preliminary results have been obtained using only 7% of the training dataset we will eventually use, leaving plenty of room for further improvements of the results.

4 Conclusions

The convolution network presented in this report provides an alternative method to the Coast Guard tool for identifying RFI in pulsar observations, and its execution is also quicker. It is currently under development, and preliminary RFI identification results are very encouraging. Although the neural network currently does not manage to flag some specific types of RFI signals such as narrow-band interferences, it actually manages to preserve a larger fraction of the actual pulsar signal. We will continue improving the neural network, e.g. by extending the training dataset or by optimizing the network's hyperparameters.

References

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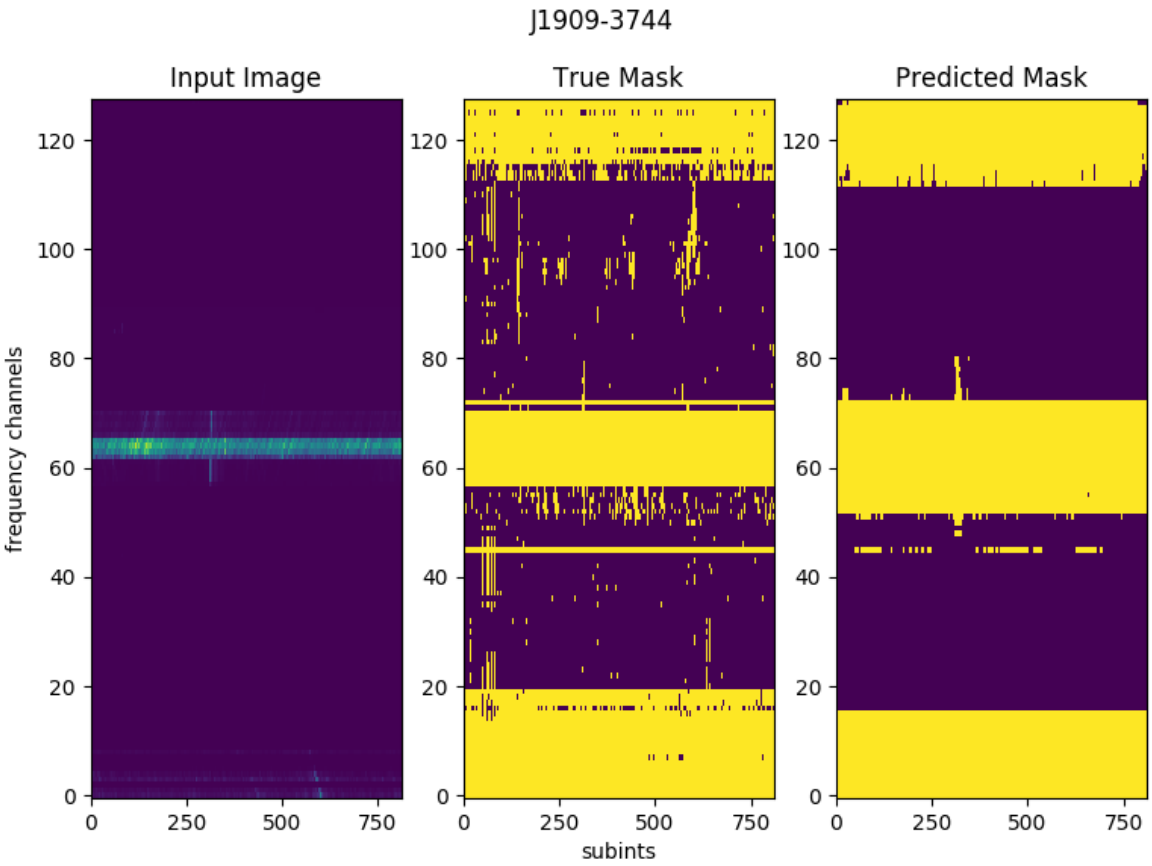

Figure 2. Preliminary results for a 1.4 GHz Nançay Radio Telescope observation of the millisecond pulsar J1909−3744. *Left panel:* dynamic spectrogram, showing the intensity of the incoming signal as a function of radio frequency and time (see text for details). *Middle panel:* Coast Guard mask for this observation. *Right panel:* preliminary mask generated with our neural network. Compared to the middle panel, although there is significant overlap in the masked channels and indices, the results are not identical.

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