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A deep neural network to restore pulsar dynamic spectra corrupted by radio frequency interference

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ABSTRACT

Radio-frequency interference (RFI) raises a challenging issue confronted by radio astronomy. This challenge is particularly pregnant when recording extremely faint signals such as those associated with pulsar observations. Indeed, generally of higher energy, RFI significantly degrades the quality of the measurements which makes astronomical data more difficult to interpret and analyze. The current solutions to tackle this problem usually consist in performing RFI flagging, i.e., localizing the time-frequency bins in the dynamic spectrum affected by interference. Then the RFI-corrupted data, i.e., the measurements associated with these identified bins, is generally discarded before any subsequent data processing, which unavoidably leads to a loss of information. Alternatively, this paper proposes to formulate RFI mitigation as a joint detection and restoration task to allow parts of the dynamic spectrum affected by RFI to be not only identified but also recovered. The proposed method relies on a particular instance of a recent architecture of deep convolutional networks. This network is trained on a large data sets generated within a simulation framework specifically designed according to physically-inspired and statistical models of the pulsar signals and of the RFI. Through extensive numerical experiments, the proposed approach is shown to reach competitive performance in terms of RFI detection and dynamic spectrum restoration.

Keywords: Radio astronomy, pulsar observations, RFI mitigation, dynamic spectrum restoration, deep learning.

1. INTRODUCTION

Pulsars are the remnants of massive stars that have collapsed, characterized by intense magnetic fields and extremely rapid, stable rotations. Beams of electromagnetic radiation emanate from their magnetic poles, sweeping through space akin to the beam of a lighthouse. Pulsars are indeed crucial objects of study in astrophysics due to their unique properties. One significant application of pulsar research is to detect and to characterize gravitational waves. However, the reliability of pulsar observations is often challenged by radio frequency interference (RFI), which contaminates dynamic spectra and hinders data analysis.

In the field of radio astronomy, the impact of RFI has emerged as a critical concern, posing significant challenges to the detection and analysis of pulsars and other celestial phenomena.

RFI mitigation techniques have already been considered to improve the quality of the data provided by radio telescopes. However the signals acquired especially in the context of pulsar observations still suffer from the presence of RFI. Conventional RFI mitigation methods like frequency excision and spectral blanking have been widely employed in various domains to suppress interference in radio frequency signals.¹ Furthermore, certain threshold-based algorithms like CUSUM² and SumThreshold³ operate on a defined threshold value. They function by summing the magnitudes of frequency components across the spectrum and then applying

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a threshold to detect and mitigate interference exceeding a specified level. These classical methods generally remain sub optimal, facing to major limitations such as incomplete identification of RFI, reliance on manual intervention, limited adaptability to evolving interference.

Since the development of deep learning over the last decade and their demonstration of superior performance when tackling vision and image processing tasks, researchers have attempted to design deep neural networks to remove RFI from astronomical data. These methods can accurately identify RFI by localizing the position RFI in the time-frequency space.⁴ However, these bins flagged as RFI are automatically discarded in the following steps of the data processing pipelines. In other words, such approaches are able to mitigate RFI by identifying the location of the RFI but are not designed to restore the astronomical data corrupted by RFI, which unavoidably leads to a loss of information.

In order to recover RFI-corrupted astronomical data in the dynamic spectra, we propose to formulate RFI mitigation as an image restoration task, which consists in the joint RFI detection and data restoration. Such an alternative approach allows for both the detection of the RFI location and the restoration of the original astronomical signals of interest. The proposed method builds on a deep neural network referred to as DRUNet⁵ which has already demonstrated its interest when performing image restoration. The architecture of DRUNet is carefully adapted to the considered task of RFI mitigation and radio astronomical data restoration. It has been subsequently trained on several realistic synthetic datasets generated according to a simulation framework specifically designed for pulsar observations. The resulting approach shows excellent performance in the restoration task, with a comparable performance to the state-of-the-art solutions currently used for the detection of RFI.

2. PROPOSED APPROACH

As described in Section 1, many present-day approaches have formulated the RFI mitigation as a segmentation or pixel-level classification task. They solve the problem of RFI mitigation by identifying the location of RFI and removing the corrupted time-frequency bins from the astronomical data. Alternatively, this paper aims at going beyond a crude RFI detection by reframing RFI mitigation as a restoration task, i.e, interpreting the RFI mitigation objective as an image denoising problem in the time-frequency space. Image denoising, a specific instance of image restoration, consists in recovering a clean image \mathbf{X} from a degraded image \mathbf{Y} and can be generally expressed as

$$\mathbf{Y} = \mathbf{X} + \tilde{\mathbf{E}} \quad (1)$$

where the noise $\tilde{\mathbf{E}}$ is assumed to be additive.

On the other hand, the dynamic spectrum \mathbf{S} recorded by a radio telescope can generally be decomposed as

$$\mathbf{S} = \mathbf{P} + \mathbf{R} + \mathbf{E} \quad (2)$$

where \mathbf{P} is the pulsar signal, \mathbf{R} is RFI signal and \mathbf{E} stands for any mismodeling and noise measurement. By comparing Eq. (1) and Eq. (2), a clear connection between image denoising and RFI mitigation. The recorded signal \mathbf{S} (resp. RFI-free signal $\mathbf{P} + \mathbf{E}$) can be interpreted as the observed image \mathbf{Y} (resp. clean image \mathbf{X}) in the context of image denoising. Furthermore, the noise $\tilde{\mathbf{E}}$ in Eq. (1) can be interpreted as the RFI signal \mathbf{R} corrupting the astronomical data in the context of RFI mitigation. Establishing this relationship between these two tasks allows the RFI mitigation problem to be tackled as an image denoising challenge. The proposed method then proposes to leverage the capabilities of deep convolutional neural networks, known for their effectiveness when performing denoising, to solve the targeted RFI mitigation problem.

More precisely, a deep neural network referred to as DRUNet is chosen as a building block of our method. DRUNet is known to be one of the state-of-the-art denoising network.⁵ This network is adapted and fine-tuned to handle astronomical data corrupted by RFI rather than natural images, e.g., corrupted by additive white Gaussian noise. The resulting so called RFI-DRUNet network is depicted in Fig. 1. It employs a widely popular encoder-decoder structure for image-to-image problems and embeds additional stacking modules with residual blocks to improved the network capabilities. The main structure and hyperparameters of the DRUNet network have been kept. Only the input and output layers of the network have been adjusted so that it can be adapted

to the RFI mitigation problem. The data used for training RFI-DRUNet comes from a simulation framework specifically designed for pulsar and RFI signals. This framework⁶ provides realistic synthetic data sets according to the model described by (2). Four different cases of simulation, denoted as C_A to C_D , are considered, each associated to a particular combinations of RFI types, where C_D stands for the more challenging case.

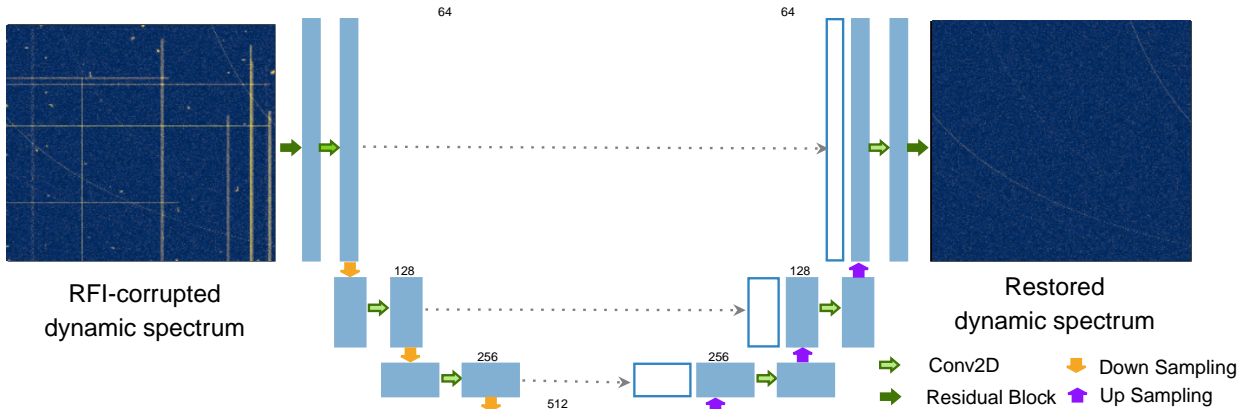


Figure 1. The structure of RFI-DRUNet. The input is the dynamic spectrum corrupted by RFI, which is shrunk in the downsampling path. The extracted features are then propagated to the upsampling path. The output is the restored RFI-free dynamic spectrum.

3. EXPERIMENT RESULTS

As mentioned in Section 2, the neural network RFI-DRUNet has been trained on a data set generated according to a dedicated simulation framework. To evaluate the proposed model performance, it has been tested on a separate data set also generated according to the same simulation protocol. The performance of the proposed method on the RFI removal problem is assessed through two main experimental objectives. The first one is its ability to recover the spectra corrupted by RFI. Since this objective is in line with a denoising problem, it has been quantitatively evaluated using an image restoration-oriented metrics, namely the peak signal-to-noise ratio (PSNR), which summarizes the similarity between the recovered spectra and the actual RFI-free spectra. The second objective of the experiments focuses on evaluating the model ability to properly identify the location of RFI, which basically brings the problem back to the current formulation of RFI mitigation and allows the proposed method to be compared to current state-of-the-art methods. Under such perspective, detection (i.e., binary classification) metrics are adopted, namely, precision, F1-score, area under receiver operating characteristic (AUROC) and area under precision-recall curves (AUPRC).

3.1 Restoration results

Four distinct cases (C_A to C_D) are considered during the training stage, which means that four distinct instances of the proposed RFI-DRUNet model have been trained, each associated to one particular simulation case. These models are denoted as M_A to M_D . During the testing stage, these four models are evaluated not only when restoring test data simulated according to the corresponding case, but also when restoring data simulated according to the others simulation cases. Table 1 reports the restoration performance of the four trained models obtained across the four cases in the test data set. In addition, the results of the PSNR were computed for the data itself in the first row, in order to illustrate the enhancement in performance achieved by the proposed RFI-DRUNet. These results indicate that the model M_A exhibits significantly different performance, delivering excellent results exclusively when evaluated on the C_A data set. This discrepancy can be attributed to the limited range of RFI nature in the training set. The algorithm struggles to identify and correct other unseen types of RFI. The models M_B to M_D perform well not only on the test sets corresponding to their corresponding training data but also demonstrate comparable restoration ability when applied to other cases.

Table 1. Restoration performance of each model, measured in term of average PSNR, computed across the four cases of testing data sets.

Model \ Data set	C _A	C _B	C _C	C _D
Data	43.17	35.02	35.87	31.92
M _A	59.43	36.38	37.77	32.89
M _B	60.15	59.81	59.88	59.22
M _C	60.36	60.01	60.12	59.51
M _D	60.41	60.18	60.19	59.95

3.2 Detection results

The outputs provided by the proposed RFI-DRUNet are converted into binary masks locating the detected RFI. This allows the proposed method to be compared to other established methods which formulate the RFI mitigation as a detection task. This process entails computing the bin-wise difference between the restored dynamic spectrum and the original input RFI-corrupted spectrum. Subsequently, a threshold is applied to this difference to produce a binary RFI mask, where a non-zero value indicates that the difference is above the prescribed threshold, i.e., a RFI has been detected. The threshold has been set to 0.15, which maximizes the F1-score of reached by RFI-DRUNet, facilitating comparisons with other methods. The performance of the method in locating the RFI has been compared to those obtained by two existing deep convolutional neural network-based methods, namely U-Net⁴ and RFI-Net.⁷ The two methods used for comparison have been also trained on the simulated dataset. To simplify the comparison, this comparison is conducted only for the training data set related to the more challenging experimental case C_D. The results are reported in Table 2. Additionally, Fig. 2 provides a visual comparison of the performance across the compared methods. These results show that the proposed method compete favorably against U-Net and RFI-Net. However, it is worth noting that RFI-DRUNet is the only one able to restore the corrupted data, as demonstrated in Section 3.1.

Table 2. Detection performance of the compared algorithms, in terms of average precision, recall, F1-score, AUROC and AUPRC.

Method	prec	rec	F1-score	AUROC	AUPRC
RFI-DRUNet	0.972	0.961	0.966	0.995	0.986
U-Net	0.858	0.987	0.917	0.991	0.926
RFI-Net	0.864	0.988	0.921	0.987	0.926

4. CONCLUSION

In this work, we formulated the problem of radio frequency interference (RFI) mitigation as a restoration task, advancing beyond conventional approaches that primarily target the detection and localization of RFI in dynamic spectra. To address this challenge, we developed a novel deep neural network, RFI-DRUNet, by leveraging and fine-tuning a widely recognized network from the computer vision literature. This network was trained using a simulated dataset generated by a sophisticated framework designed to produce realistic simulations of both RFI and pulsar signals. Our experimental results demonstrate that RFI-DRUNet excels in both restoration and detection tasks. Specifically, the network effectively reconstructs clean signals from corrupted data and accurately identifies RFI, outperforming traditional methods. Future work will focus on optimizing the deep network to reduce its computational complexity, with the goal of enabling real-time processing.

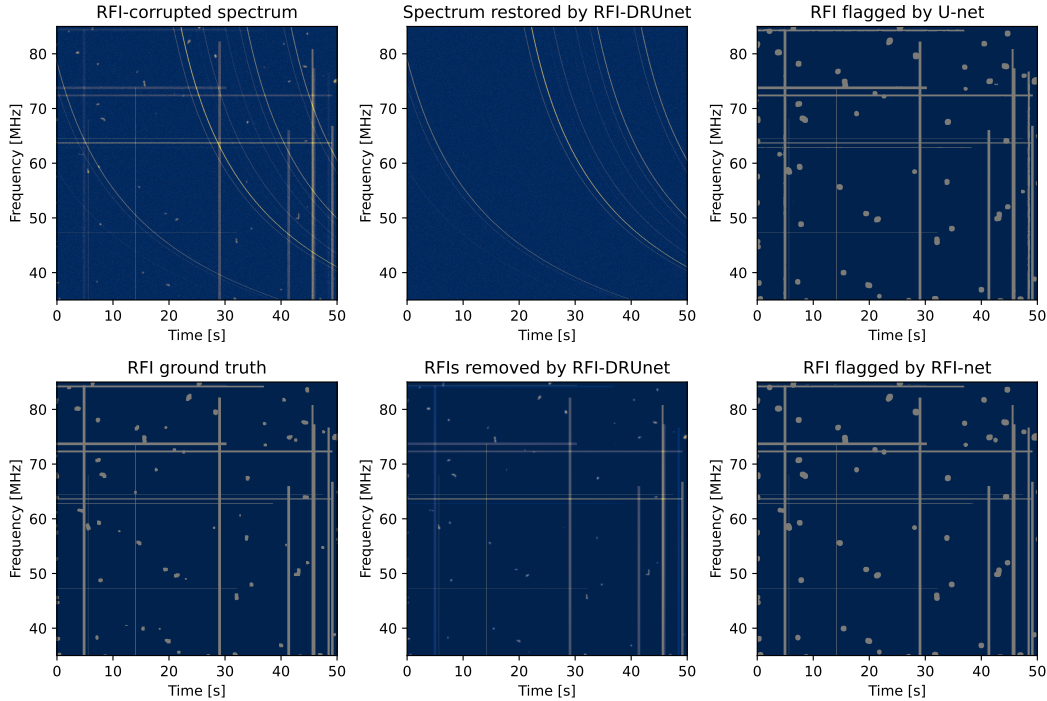


Figure 2. Visual comparison of results obtained from the compared methods.

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