Detection of Radio Frequency Interference in Radio Astronomy Using Deep Neural Networks

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Abstract

Radio astronomy is the field of study concerning the analysis of radio-frequency radiation originating from celestial bodies. In this field, measurements of stars, galaxies and other astronomical sources are measured by their radio frequency emissions. Radio frequency radiation comes mostly from non-thermal radiation due to synchrotron radiation or electronic transition. This process is susceptible to interference resulting from proliferation of wireless communication technologies, satellites and aircrafts, wind turbines, etc. Radio-frequency interference (RFI) is a electromagnetic disturbance that occurs in the radio-frequency spectrum that causes the degradation of signal quality in a system. These disturbances may be caused by both man-made and natural sources and effect various electromagnetic systems such as radars, mobile phones as well as radio-telescopes. These strong radio signals vary in both time and frequency domains and disturb the radio telescope outputs, therefore adding artifacts to the final readings. The difference in the magnitude of the power received from RFI and the observed astronomical sources cause corruptions in areas of the data that cannot be recovered. Although preventive measures like constructing radio telescopes in remote locations, ground shielding and employment of band-pass filters reduce RFI considerably[1], these methods do not prevent all RFI. Therefore, methods to identify and mitigate interference are of high importance to the radio astronomy communities.

There are a variety of methods available in the literature to deal with RFI. These methods fall into three categories: Linear models, statistical methods and machine learning-based methods. In linear methods, techniques like Singular Vector Decomposition and Principal Component Analysis are used to identify RFI [2, 3]. These methods do not perform well on signals with non-linear and stochastic characteristics. The second category of RFI detection methods is based on the assumption that the characteristics of RFI in the time-frequency domain is different than that of the astronomical signal. Typically, the recorded astronomical sources appear as smooth over longer durations of time, while RFI usually has much higher power and is localized. One of the most notable methods in this area is AOFlagger [4]. Assuming most RFI are scale-invariant in time and/or frequency domain, AOFlagger uses *Scale-Invariant Rank* operator to identify interference. This method has been widely and successfully used to identify and mitigate interference [5, 6]. Nevertheless, due to variability of the structure of particular RFI signals, creating an analytical model of them is a challenging task[7]. In recent years, with the success of artificial intelligence and machine learning in classification and pattern recognition tasks, a number of ML-based methods have been proposed to address the RFI problem which will fall into the third category above. Especially with the development of deep neural networks and deep learning methods, there has been a surge in the performance and scale of certain pattern recognition and object detection tasks [8, 9]. Certain types of deep neural networks like Convolutional Neural Networks, used for object detection, don't need prior knowledge of the target objects, which makes them especially suitable to detect RFI signals from multiple sources. Therefore, it's not surprising that there have been a number of methods presented in literature for RFI detection using deep neural architectures[1, 10, 13].

In the presented work, we propose a framework to identify RFI in LOFAR correlated data. The proposed framework defines the task as a two-class image segmentation problem and incorporates U-Net deep neural network architecture[11] to solve the problem. The main contributions of this work are superior performance and use of non-synthetic observation data obtained from LOFAR long time archive for training and testing of the model. We use CPU and GPU resources of DAS-4 and SURFLisa compute facilities to train out deep neural network. In convention with classification-based research, this work is evaluated through the use of F1-score, recall and precision. We show a highly accurate detection of RFI with comparable or better results compared to reported results in the literature, test-time detection performance comparable or superior to current statistical tools like AOFlagger and the feasibility of the proposed system to be incorporated into available online workflows[12].

Keywords— RFI, Radio Frequency Interference, Deep Neural Networks, U-Net

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