Detection and Mitigation of Radio Frequency Interferences while Observing Pulsar Stars

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ABSTRACT

While observing signals from astronomical sources, radio astronomers are required to alleviate the effects of man-made radio sources such as cell phones, satellites, aircraft, and observatory equipment. Radio frequency interference often occurs as short bursts (within a millisecond of time) across a broad range of frequencies, and can be confused with signals from sources of interest such as pulsars. With increasing amount of data produced in the observatories, automated strategies are required to detect, classify, and characterize these short transient RFI events. We aim to design a self-learning approach in which the algorithm is able to detect & create mitigation filters for RFI.

Keywords: RFI -Radio frequency interference, Spectrogram – signal in represented in domains of time & frequence

I. INTRODUCTION

Radio-frequency interference (RFI) is an Electromagnetic interference (EMI) when the radiations are in radio frequency spectrum. It is a disturbance generated by an external source that affects an electrical circuit by electromagnetic induction, electrostatic coupling, or conduction. The disturbance may degrade the performance of the circuit/antenna or even stop it from functioning. In the case of a listening to radio data, these effects can range from an increase in error rate to a total loss of the data. Both man-made and natural sources generate changing electrical currents and voltages that can cause EMI. Few examples are automobile ignition systems, cell phones, thunder storms, the Sun, and the Northern Lights. EMI frequently affects AM radios. It can also affect cell phones, FM radios, televisions and even radio tele-scopes.

The problem of RFI has been there for quite a while and scientists have worked around to develop several algorithms to detect and classify RFI. In an algorithm called spectrogram calculation, radiometric signals are assumed to be sampled at an adequate sampling rate satisfying the Nyquist criterion and the spectrograms are obtained from these discrete time signals. Similarly, in Wiener Filtering, the spectrogram of a noise signal with sinusoidal interference signals can be considered as a noisy image, where the noise is the spectrogram of the radiometric signal (the one we want to measure), and the image to be detected is the spectrogram of the interference (the one to be canceled). Therefore, designing a filter to eliminate the noise from the image is the way to estimate the RFI, for a later removal of the interference without loss of the radiometric data. Another algorithm called smoothing algorithm, works on the principle that the most obvious way to detect the presence of interference in a radiometric signal is by detecting power peaks in the received signal that are larger than the variance of the measured thermal noise in the absence of RFI. This detection can be performed either in both the time and frequency domains.

While collecting radio signals from astronomical sources, radio astronomers face a serious challenge of mitigating the effects of radio frequency interference (RFI) resulting from man-made radio sources.

Examples of such sources include cell-phones, satellites, aircraft, and on-site observatory equipment. As the volume of data collected and prevalence of RFI sources increases, automated mitigation of RFI becomes increasingly important. The idea encourages us to design a deep learning approach to automatically detect and mitigate the RFI. This report explains the approach and future outcomes of it. The approach adopted uses supervised deep learning to allow large volumes of data to be processed accurately.

Problem Statement:

Given the spectrogram of observed radio signal, the model should detect and generate mitigation filters for two types of interferences:

1) Short impulses in a band of frequencies
2) Long period interference at a single frequency

II. THEORY

Pulsar characteristic pulse

Pulsars are highly magnetised rotating stars, which emits a beam of EM radiation along their axis of rotation. Because of their rotating angular momentum, their EM beams swivel around their axis of rotation of the angular momentum. When these beams point towards the Earth, we see a pulse of EM radiation. But these pulses when reached at the Earth, becomes stretched out because of the frequency-dependant index of refraction of the interstellar media. Because of this dispersive nature, the pulsar’s pulse is seen as a chirp in the spectrogram. A chirp is a signal in which the frequency increases or decreases with time.

Interferences

Short impulses in a band of frequencies

This interference exists only for very small time, yet produces noise in a wide range of frequencies. In a spectrogram this can be ideally recognised by a vertical stripe along the frequency-axis (y-axis). The range of the stripe indicates the band of interference frequencies. A correct mitigation filter will flag the entire frequency band and the pulse duration of the signal.

Long period interference at a single frequency

When a source keeps on emitting a signal for a long time in a very narrow band of frequencies, it generates a horizontal stripe on the spectrogram.

Here, we are trying to mitigate the interference in the signal by marking/flagging the RFI regions of spectrogram. So, our algorithm must produce a mitigation filter the size of the input spectrogram, which requires our model to output an image (filter) the same size as of the input.

The problem is very much similar to image segmentation and classification. First, the model extracts the features from the input. In the next phase, the model reconstructs an image from the extracted features. This is the phase where the model is trained to reconstruct only some intended features.

U-Nets

U-Nets (shown in Figure 1) are the best match for this type of necessity. They are an amalgamation of contracting and expanding convolutional layer models. The contracting block of the model extracts the features while the expanding block makes use of the

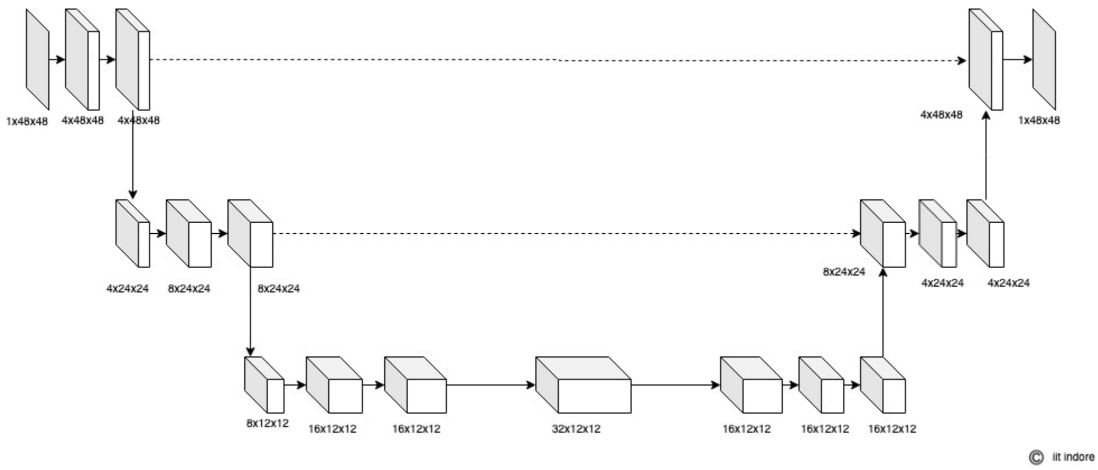

Figure 1: U-Net for RFI Mitigation against pulsar detection

1) Right arrow: Convolution 2) Bottom arrow: Pooling 3) Up arrow: Up pooling 4) Dotted: Layer addition

extracted features and previous layers activation maps to generate a new image.

In this experiment, U-Net model should extract all the features (signals, both original and interference) and from these features it reconstructs the mitigation filter.

III. EXPERIMENTATION

Like every other machine learning algorithm, deep learning algorithm also require three sets of data, training data, validation data and testing data. This creates a tremendous requirement for a properly formatted, algorithm-digestive data. Thus, experimentation involves two phases

Synthesizing the data

Due to the lack of availability of human labelled original data, synthesized data is used for training purposes.

Sample data:

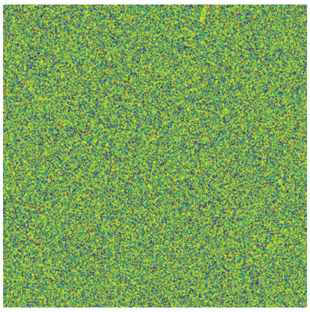

Figure 2: Synthesized spectrogram without any signal

This no-signal spectrogram is generated using random values from 0 to 1. In general the background noise picked up by antenna will show small thread patterns in the spectrogram.

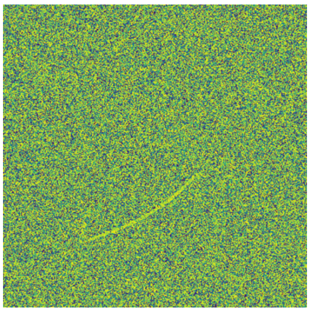

Figure 3: Synthesized spectrogram with pulsar's signal.

Figure 3 contains a simulated chirp signal.

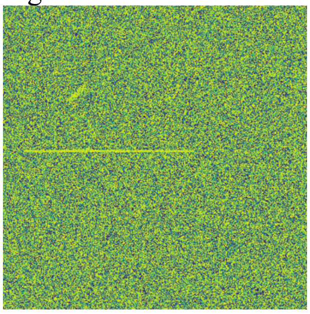

Figure 4: Synthesized spectrogram of long period interference at a single frequency (seen as a horizontal line)

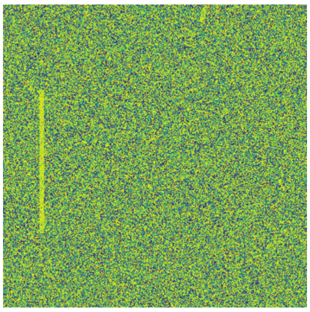

Figure 5: Synthesized spectrogram of short impulse interference containing wide range of signal frequencies (vertical line)

To train the U-Net, we also need the expected output for a simulated input (signal spectrogram). The input and output simulated pair look as follows:

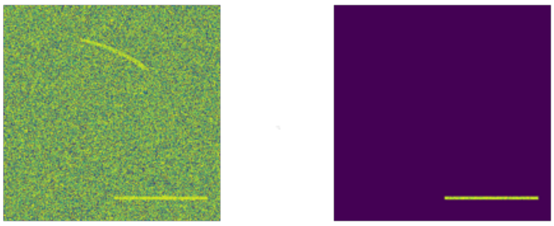

Figure 6:
a) Left image shows a sample input containing pulsar signal and a single-frequency long duration interference
b) Right side one shows the target image used for training.

Note that in Figure 6.b, the target image contains a mask only on the interference and not on the pulsar signal. This is because, the U-Net should be trained to only mask interference and not the pulsar signal.

Design of Neural Network and Training

Since the U-Nets are purely made of convolution layers and sampling layers, they are size invariant, meaning that, any size of spectrogram can be used for generating the mitigation filter.

Here is the U-Net model in detail:

Layer #	I. Layer Details		
	Layer Type	**Filter size**	**#filters**
1,2	2D Convolutional + BN + Activation	3 x 3	4
3	Pool down	2 x 2	-
4,5	2D Convolutional + BN + Activation	3 x 3	8
6	Pool down	2 x 2	-
7,8	2D Convolutional + BN + Activation	3 x 3	16
9	2D Convolutional + BN + Activation	3 x 3	32
10	Upsample(2x2) + Concat prev. layrer + Dropout	3x3	32
11,12	2D Convolutional + BN + Activation	3 x 3	16
13	Upsample(2x2) + Concat prev. layrer + Dropout	3x3	16
14,15	2D Convolutional + BN + Activation	3 x 3	8
16	Upsample(2x2) + Concat prev. layrer + Dropout	3x3	8
17,18	2D Convolutional + BN + Activation	3 x 3	4
19	2D Convolutional + BN + Activation	3 x 3	1

Loss Function

To train the model and to drive the back propagation, we need a robust loss function.

It is as follows:

$$loss = (1 - sum(x.y)/sum(x))^2 + (sum((1-x).y)/sum(1-x))^2$$

where x is the predicted output, while y is the actual output.

The first term rewards the network by decreasing the loss based on the matched pixels while the second term increases the loss if there are un-matched pixels.

The training was performed on thousand 20x20 pixel images. Large number of small sized images were chosen so that the model learns different shapes in less computation steps.

IV. RESULTS

The trained U-Net is tested both on the simulated data & the actual data.

On simulated data:

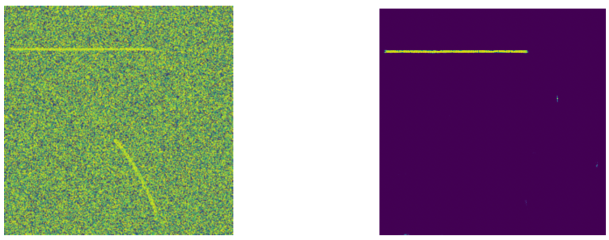

Figure 7: For a spectrogram containing both pulsar signal and RFI, the mitigation filter was marked only for RFI

On actual data:

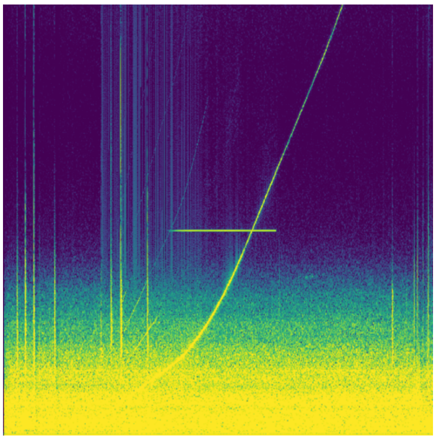

Figure 8: Spectrogram containing
a. constant freq. interference
b. multiple frequency band impulses (interference)
c. and an increasing chirp

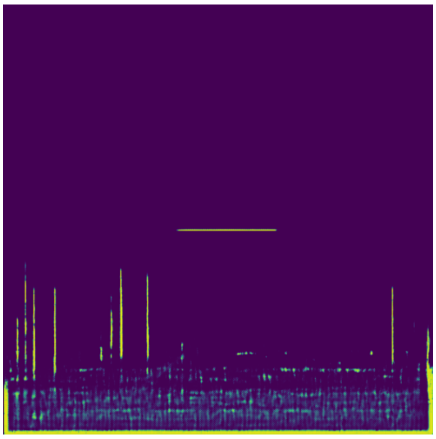

Figure 9: The generated mitigation filter correctly flags both the types of interferences, but allows the chirp to go unmarked.

Mitigation of RFI can be performed on the original signal using simple operations like addition, subtraction and convolutions.

Here is a side by side comparison of original signal and RFI mitigated signal.

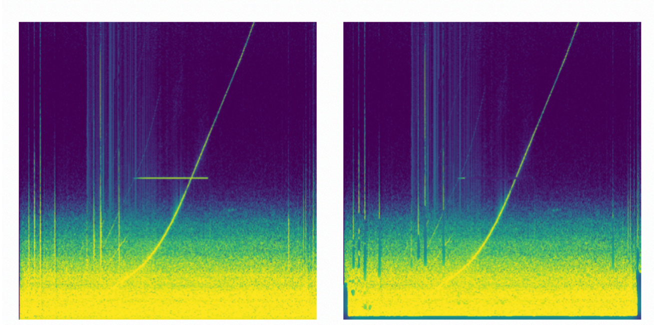

Figure 10: a) Left side- original signal b) RFI Mitigated signal

The horizontal interference pattern becomes completely invisible in the mitigated signal. As well as, the sharp vertical stripes in the left side of the image was partially removed.

V. CONCLUSION

Interferences limits the capability of studying or searching for pulsar emitted signals. Here, we have developed and implemented a model to mark all the unnecessary interferences in the input. Further the marked data was removed from the original signal, to help boost the efficiency of Pulsar detection and studying.

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