

U-NetIM: An Improved U-Net for Automatic Recognition of RFIs

Min Long,¹ Zhicheng Yang,² Jian Xiao,² Ce Yu,² and Bo Zhang³

¹*Boise State University, Boise, United States of America*

²*Tianjin University, Tianjin, China; xiaojian@tju.edu.cn*

³*Chinese Academy of Sciences, Beijing, China*

Abstract. Radio frequency interference (RFI) mitigation is a key phase in data processing pipeline of radio telescopes. Classical RFI mitigation methods depending on the RFI physical characteristics can often fail to recognize some complicated patterns or result in misrecognition. We developed a novel approach of RFI recognition and automatic flagging using an improved convolution neural network. The improved U-Net model (U-NetIM) is constructed based on U-net with much deeper network structure for more complicated patterns and more components to reduce recognition error caused by over-fitting. The experiments show that the U-NetIM has better performance on both precision and recall rate than SumThreshold the most widely used classical method, U-Net, a traditional deep learning model and KNN, a typical machine learning model.

1. Introduction

Recognizing and marking the radio frequency interference (RFI) is a key step in the data processing of radio telescope observations. However, in the traditional recognizing process, manual intervention is often required, which greatly affects the efficiency of data processing. This paper aims to explore the application of deep learning technology in the automatic RFI recognition and provide a technical reference and application for the optimization of data processing systems adopted by large radio telescopes such as Five-hundred-meter Aperture Spherical radio Telescope (FAST).

RFI refers to any unwanted signal entering the radio telescope receiving system Mosiane et al. (2017) and has variety of manifestations. Some RFI are very scattered in spectrum, affecting a wide range of channels (e.g., wideband); some appear to be concentrated, affecting only certain channels (e.g., narrowband). Meanwhile, the RFI can be instantaneous, burst-like pulse (high intensity, short time), or it can occur continuously over a period of time, like standing waves (intensity changes periodically with time). Most RFIs are much stronger than common astronomical signals. If the received signals consist of vertical or horizontal envelopes of a wide or narrow band, (i.e, discrete or high-intensity occurrence), it is very likely to be contaminate by RFIs and causes misrecognition.

Current methods of RFI recognition can be mainly divided into the categories of linear detection, threshold-based algorithms, machine learning and deep learning methods. For the RFI with repetitive features in the time-frequency domain, like standing waves, the linear detection methods can achieve very good results. However, it fails in recognizing more complex signals, such as irregular signals generated by satellite

operation. The threshold-based algorithm has a good performance on discrete RFIs when the observation background is relatively stable. The SumThreshold Offringa et al. (2010) is the most widely used threshold-based algorithm in the existing radio data processing. However, when a very large number of RFIs are present, affecting most channels, the threshold-based algorithm will be less effective. The artificial intelligence methods represented by machine learning and deep learning have been widely used in image recognition, nature language processing, etc., and may can provide improvements for the automation and accuracy of RFI recognition.

2. Deep Learning Modeling

The recognition of RFI means to search for regions with significantly increased intensity or certain special features on the time-frequency plane that are similar to the image. The network model used to process image is mainly Convolutional Neural Network (CNN). The CNN is named after the convolutional operation that multiplies all the values in the region covered by the convolutional kernel and then adds them together. The shallow layers extract the texture information of the image. And then the deep layers integrate the features from the shallow layers for the semantic information. The Pooling layers are used to filter the information. Finally, through multiple convolutions and pooling layers, specific information about certain areas of the image is obtained and then marked.

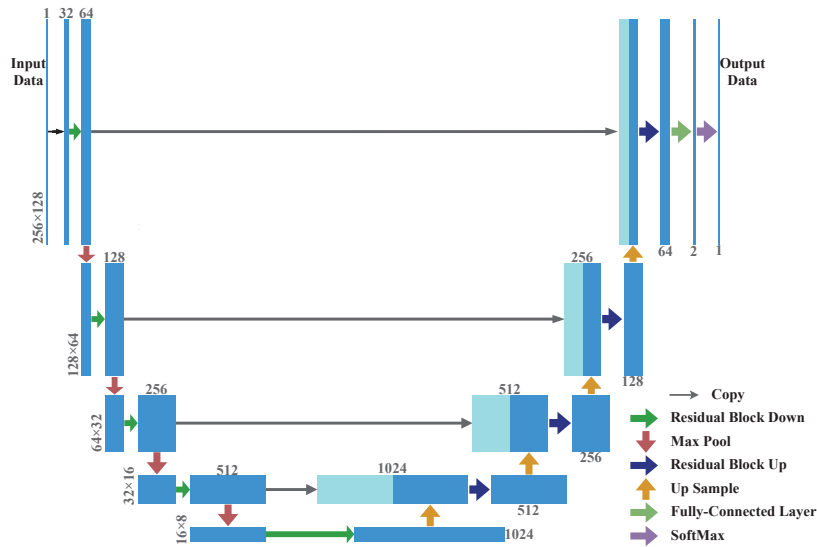


Figure 1. Network architecture of the proposed U-NetIM model. Blue boxes represents multi-channel feature map with the number of channels denoted on the top and the x-y-size to the left. The arrows denote the flow of operations.

This paper proposed an improved U-NetRonneberger et al. (2015) model (U-NetIM) of RFI recognition considering the features of the RFI discussed above. More layer are added to the network to obtain more information form the data for complex RFI.

For the narrow band RFIs, they challenge more precise searching and thus small convolution kernels of size 3 are used. As for wide band RFI, multi-layer convolution is used to expand the convolution field of view. Since RFI appears intensely, while the background is relatively stable, it is very suitable for Max-pooling to retain more changed information. Moreover, the random RFI may make the data distribution vary greatly. Therefore Batch-Normalization is used to scale the data to make the distribution more stable for better recognition performance.

The proposed U-NetIM model is shown in Fig. 1. The left side of the model is the down-sampling path, the data enters from the upper left corner, and the result of each operation (colored arrow) is subjected to the Max-pooling operation. Meanwhile the results are sent to the corresponding layer in the up-sampling path as copies. After four operations, the data comes to the bottom of the model, which is followed by the up-sampling path on the right. The up-sampling path is combined with the information extracted from the down-sampling path to gradually mark the RFIs on the original data. After the up-sampling path, the data will reach the upper right corner with the same size as the input data. After that, the channels of data are reduced to 2 via a fully connected layer and Softmax operation, which represents the RFI category corresponding to each pixel. Finally, the category is taken as the output result.

3. Experiments and Results

This paper tested the U-NetIM model and compared the results with traditional methods, such as U-Net, KNN, and SumThreshold, in aspect of the accuracy and efficiency of RFI recognition. The experiment used simulation data generated by HIDE Akeret et al. (2017). The data set is divided into astronomical data as input data and Ground_Truth as standard recognition results. The Loss is calculated from the output data produced from neural network and the Ground_Truth. The data set consists of 2 parts, 2900 training data and 76 test data.

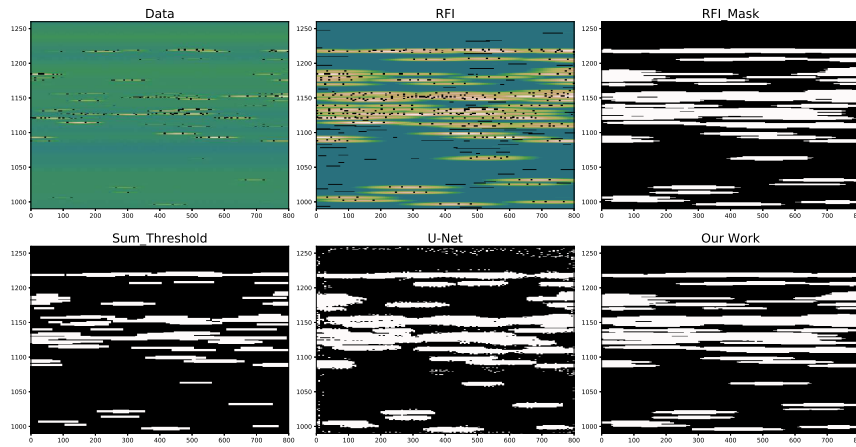


Figure 2. Comparison of experiment results of RFI recognition methods. The white zones represent recognized RFIs that is compared with accurate RFI patterns

The experiment results are shown in Fig. 2. It can be seen that the recognition result of the U-NetIM is closest to Ground_Truth (RFI_Mask), the most of RFI patterns have been correctly labeled and little misjudge occurs.

The recognition results are then further evaluated using synthetic indicators, as shown in Fig. 3. First, it can be seen that the U-NetIM achieves the highest scores for all indicators. It can not only identify more accurately, but also more completely. Second, it clearly shows that two deep learning methods (U-NetIM and U-Net model) have better performance than the traditional ones (KNN and SumThreshold) in RFI recognition. Compared to the U-Net model, U-NetIM can achieve higher recognition accuracy without sacrificing false detection rate.

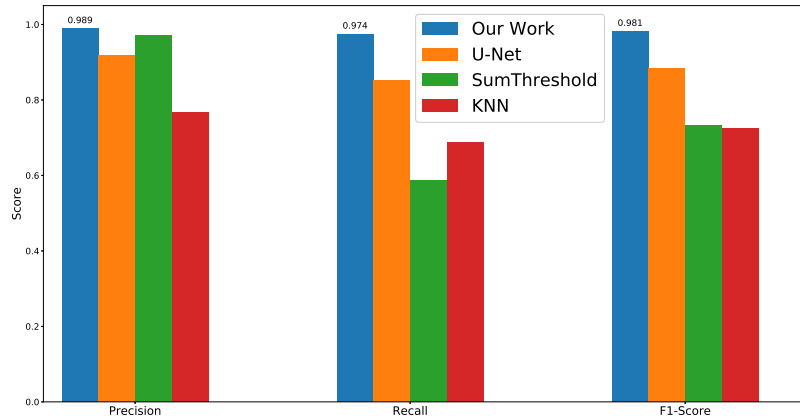


Figure 3. Evaluation of experiment results with indicators of precision, recall and F1-score. U-NetIM has the best scores in all aspects of evaluation

The better performance in deep learning methods is mainly due to a fact that the deep learning is very capable for nonlinear problems. It adopts the nonlinear activation function "ReLU", which makes it more competent for more complicated tasks. Since most form of RFIs are nonlinear, in addition, the range and size are always different, it's a challenge for the traditional methods (such as SVD) to retain good results compared to U-NetIM.

Currently, there is still room for improvement of the speed of running U-NetIM RFI recognition. In order to be able to effectively process upcoming large data set from the FAST radio telescope, the next work needs to improve the speed of recognition.

Acknowledgments. This work is supported by the Joint Research Fund in Astronomy (U1731125, U1531111) under a cooperative agreement between the National Natural Science Foundation of China (NSFC) and Chinese Academy of Sciences. M.L. thanks to the support of startup fund at Boise State University.

References

- Akeret, J., Seehars, S., Chang, C., Monstein, C., Amara, A., & Refregier, A. 2017, *Astronomy and Computing*, 18, 8
- Mosiane, O., Oozeer, N., Aniyan, A., & Bassett, B. A. 2017, in *Materials Science and Engineering Conference Series*, vol. 198, 012012
- Offringa, A. R., de Bruyn, A. G., Biehl, M., Zaroubi, S., Bernardi, G., & Pandey, V. N. 2010, *MNRAS*, 405, 155. 1002.1957
- Ronneberger, O., Fischer, P., & Brox, T. 2015, *ArXiv e-prints*, arXiv:1505.04597. 1505.04597