An improved U-Net for Automatic Recognition of Radio Frequency Interference

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Abstract. Radio frequency interference (RFI) mitigation is a key phase in data pipeline of radio telescopes. Classical RFI mitigation methods depend on the RFI physical characteristics, often fail to recognize some complicated patterns or result in misrecognition. We developed a novel approach of RFI recognition and automatic flagging with an improved convolution neural network. The network was 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. Compared to the most widely used classical method – SumThreshold, our method has better performance on both precision and recall rate, it also outperformed the 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 for the optimization of data processing systems for large radio telescopes such as FAST. [1]

Radio Frequency Interference (RFI) refers to any unwanted signal entering the radio telescope receiving system Mosiane et al. (2017). Some RFI are very scattered, affecting multiple channels (wideband); some appear to be concentrated, affecting only certain channels (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 signal consists of vertical or horizontal envelopes of a wide or narrow band (discrete or high-intensity occurrence), it is very likely to be contaminate by radio frequency interference.

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At present, the methods of RFI recognition can be mainly divided into linear detection, threshold-based algorithms, machine learning and deep learning. If the RFI has repetitive features in the time-frequency domain, like standing waves, linear detection can achieve better results. But it cannot recognize more complex signals (such as irregular signals generated by satellite operation). The threshold-based algorithm has a good effect on the discrete RFI 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. At present, artificial intelligence represented by deep learning has been widely used in image recognition, nature language processing, etc., which may improve the automation and accuracy of RFI recognition.

2. Deep Learning Modeling

The recognition of RFI is to find areas with significantly improved intensity or some certain special features on the time-frequency plane which are similar to image. The network model used to process image is mainly Convolutional Neural Network (CNN). The CNN is named after the convolutional operation which 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.

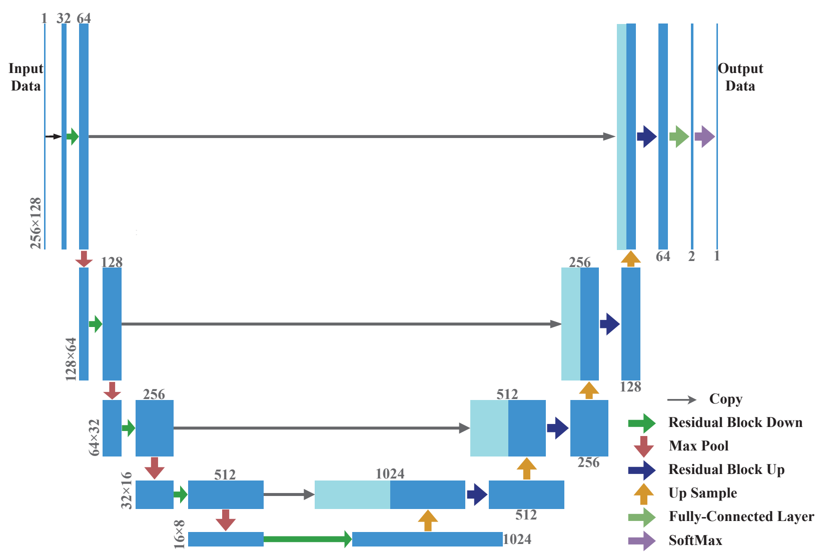

Figure 1. Network structure of the model

Considering the feature of the RFI, the corresponding structure are developed. The neural network in this paper is based on the U-Net network Ronneberger et al. (2015). More layer are added to the network to obtain more information form the data for complex RFI. Because there is narrow band RFI, it should be more precisely when looking for it. Therefore, 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 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 model is shown in Figure 1. The left side of the model is the down-sampling path, the data enters from the upper left side, 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 RFI on the original data. After the up-sampling path, the data will reach the upper right side of the model which is the same size as the input data. Finally, the channels of data are reduced to 2 via a fully connected layer and Softmax operation, which represents the the RFI category corresponding to each pixel. Finally, the category is taken as the output result.

3. Experiment and Result

This paper has carried out experiments on the proposed model. At the same time, some traditional methods have appeared in this paper to compare the performance of RFI recognition. The U-Net, KNN, and SumThreshold methods are reproduced here. 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.

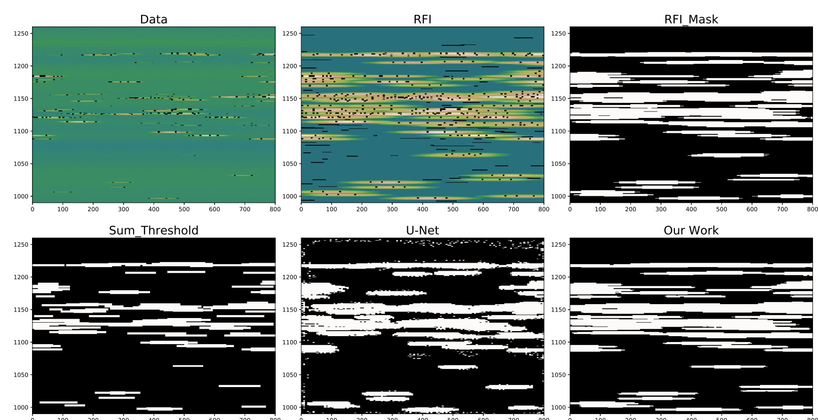

Figure 2. Experiment result in images

The experiment results are shown in Figure 2. It can be seen that the recognition result of the method in this paper is closest to Ground_Truth (RFI_Mask). Data belonging to the RFI are basically correctly labeled, and other data misjudged is not much. Other methods are more or less awkward.

Next results are summarized and evaluated with indicators, and then visualized. Some indicators are plotted as a histogram. It can be seen that our works achieve a good effect. Compared with other methods, the model has achieved a higher score in all indicators. It can not only identify more accurately, but also more completely. It can also be seen from the Figure 3 that the deep learning method (this model and U-Net model) is better than the traditional methods (KNN and SumThreshold), Demonstrating the advantages of deep learning methods in RFI recognition. For comparison in deep learning, this model can achieve higher recognition accuracy without sacrificing false detection rate. Meanwhile the area under curve (AUC) indicates the model has better performance on recognition than the U-Net model. Furthermore, the curve of this model is smoother, meaning that there is no much over-fitting.

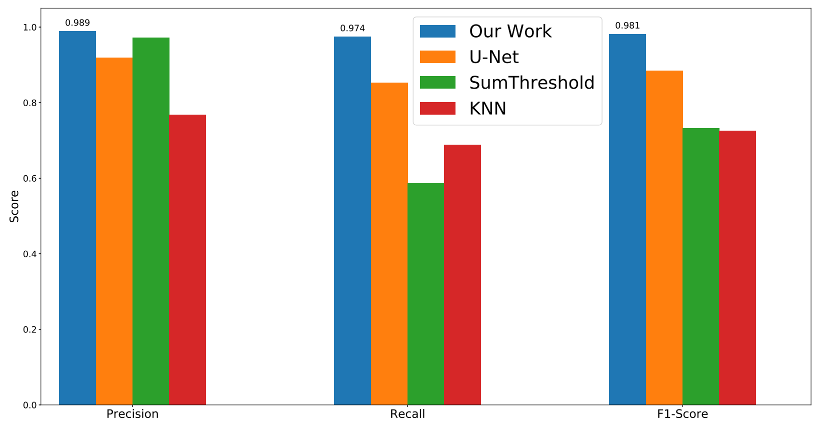

Figure 3. Experiment result in Histogram

After research, there are some common reasons for better deep learning performance. Deep learning has greater advantages for nonlinear problems than traditional ones. The deep learning model use the nonlinear activation function "ReLU", which makes it more competent for more complicated tasks. Since the RFI has various forms, most of which are nonlinear forms, the range and size are always different, the traditional methods (such as SVD) cannot get good results. However, at present, this model can achieve a better effect, but the speed is slower. In order to be able to effectively use the FAST radio telescope data processing flow in the future, the next work needs to improve the speed of recognition detection.

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