Radio frequency interference detection based on the AC-UNet model

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Introduction

In radio astronomy, radio frequency interference (RFI) broadly refers to the influence of human communication activities and natural interference signals that affect the reception of weak astronomical signals by radio telescopes。Therefore, it is very important to effectively process the complex radio astronomical observation data and perform RFI detection.

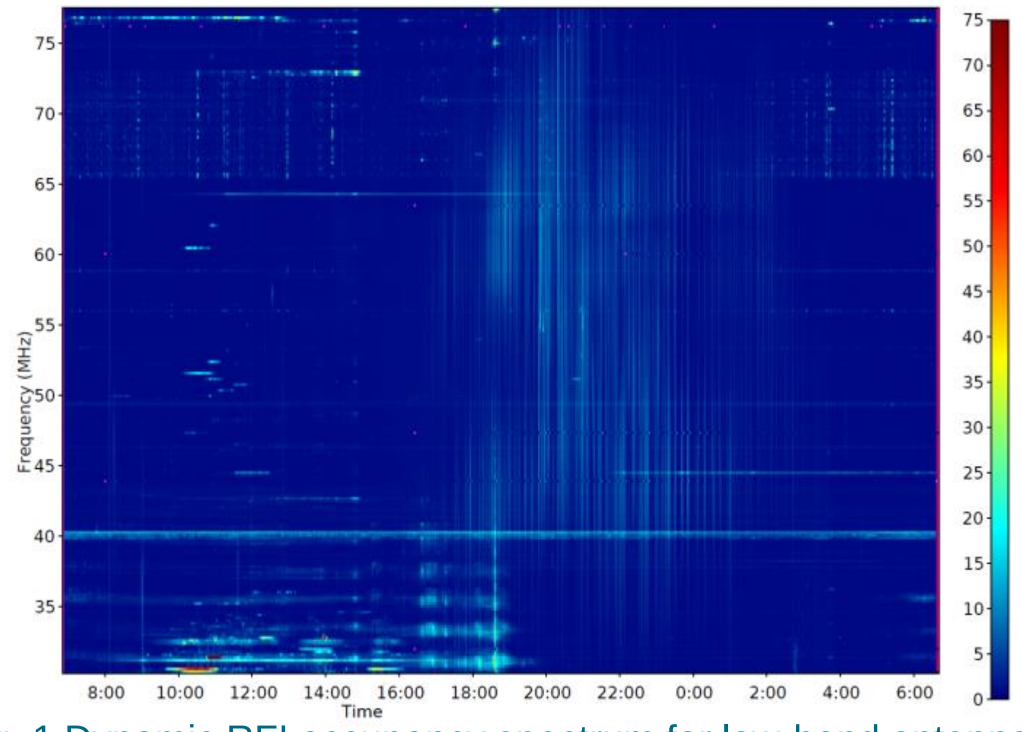

Fig. 1 Dynamic RFI occupancy spectrum for low-band antennas (LBA) surveys. Color intensity represents RFI occupancy, from 0% to 100%

Objectives

In the task of RFI detection, RFI is often flagged in the form of points and lines. We also hope to get the location of RFI and get the corresponding flag. The traditional flagging method or flagging based on human experience is inefficient. In addition, automatic and efficient data processing methods are needed in massive data astronomical observations, especially for large area sky surveys or high time resolution observations.

➢ **objective one:**

Accurately and comprehensively perform RFI detection on images with a small amount of RFI.

➢ **objective two:**

Improve the efficiency and recall rate of RFI detection, and be able to effectively learn the characteristics of RFI images.

Methods

☐ The proposed model adds 14 atrous convolution layers (AC layer) on the basis of U-net, called AC-UNet.

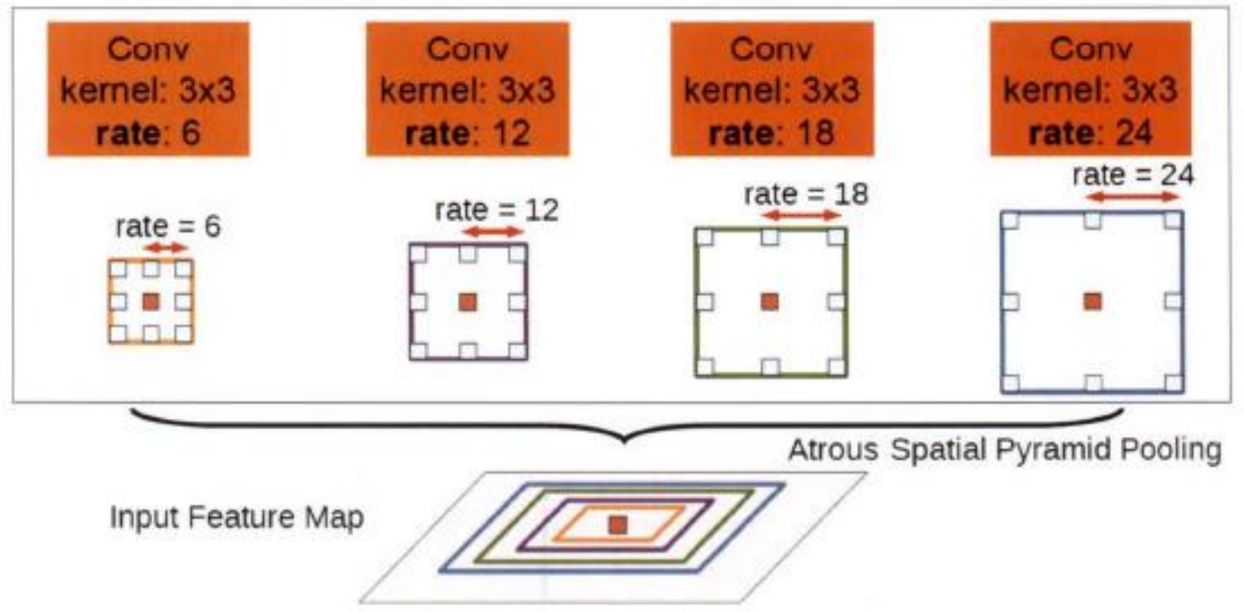

Fig. 2 ASPP schematic.

To classify the center pixel (orange), ASPP exploits multi-scale features by employing multiple parallel filters with different rates. The effective field-of-views are shown in different colors

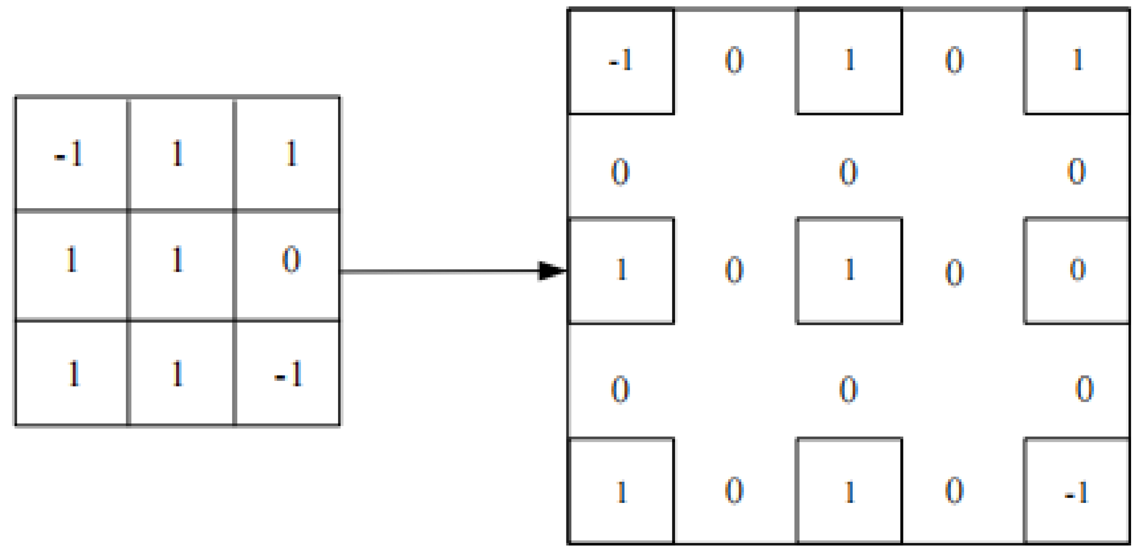

Fig. 3 Convolution kernel expansion process when the expansion coefficient is 2. Left: the original convolution kernel. Right: the expanded convolution kernel.

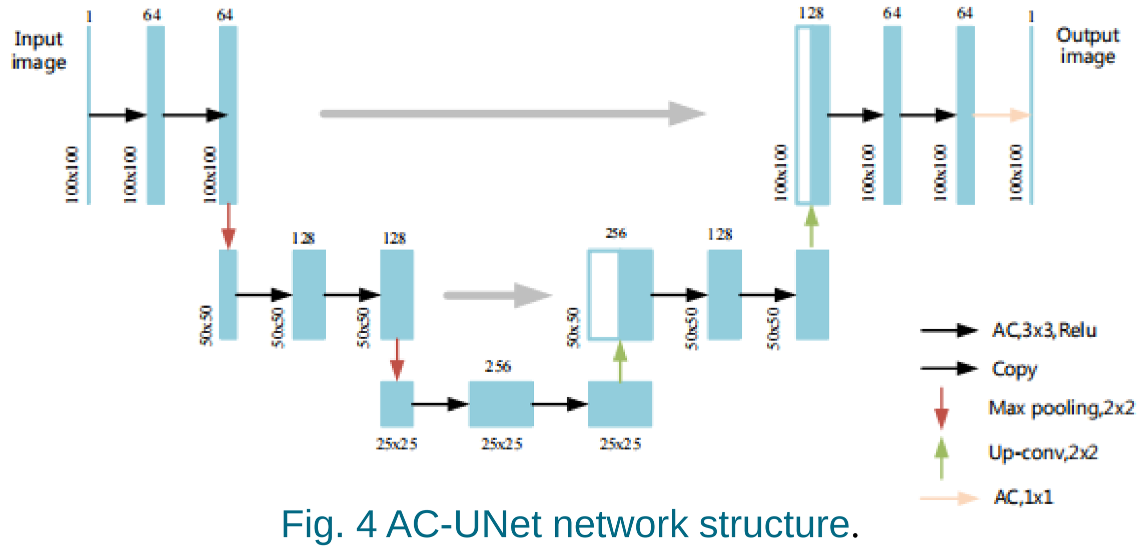

Fig. 4 AC-UNet network structure.

Experiment and Discussion

✓ *Dataset*

No.	False Number	True Number
694	9668	332
518	9599	401
510	9521	479
512	9515	485
1087	9250	750

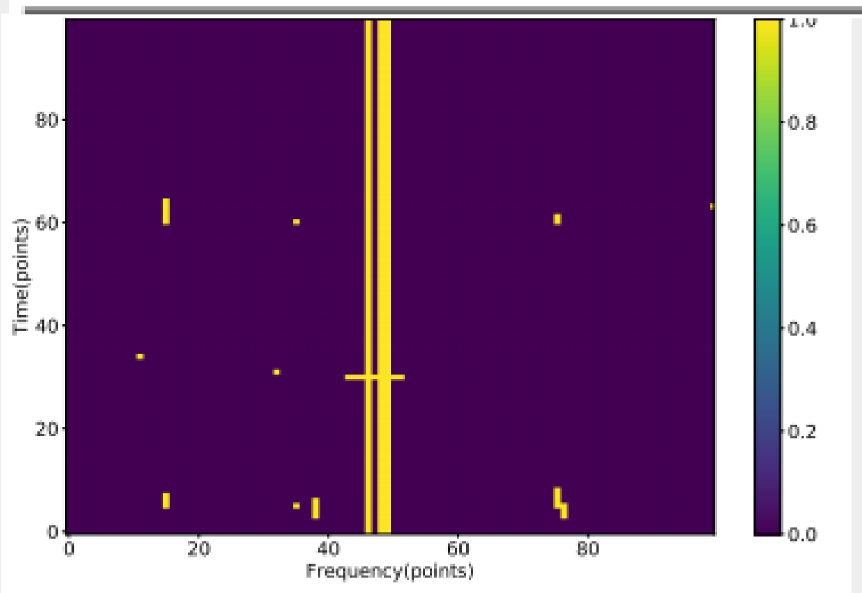

Fig. 5 Data block 694 raw RFI flag.

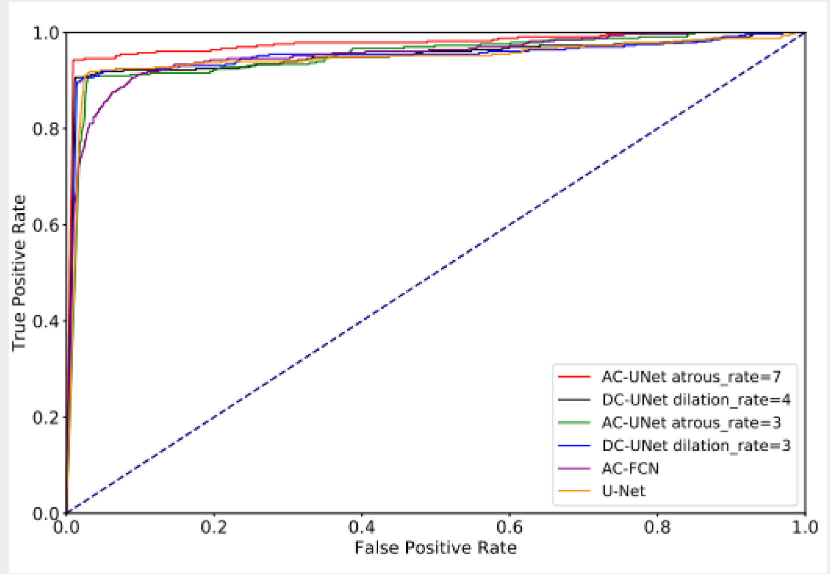

Fig. 6 ROC curve of the classification effect of each model on data block 694.

The closer the ROC curve is to the coordinate point (0, 1), the better the classification prediction effect for each point. AC-UNet is better than other methods.

Results and Discussion

We use data blocks 694, 510, 512 with less than 500 RFI, and randomly select the results of two other test samples 518, 1087 data blocks for display.

Network Model	Classification	Recall Rate	F1-Score	AUC
U-Net	False	0.98	0.99	0.89
	True	**0.81**	**0.66**	
	avg/total	0.97	0.97	
DC-UNet dilation_rate=3	False	0.99	0.99	0.77
	True	**0.56**	**0.63**	
	avg/total	0.98	0.98	
AC-UNet atrous_rate=3	False	0.97	0.99	0.94
	True	**0.90**	**0.68**	
	avg/total	0.97	0.98	
DC-UNet dilation_rate=4	False	0.98	0.99	0.94
	True	**0.90**	**0.72**	
	avg/total	0.98	0.98	
AC-UNet atrous_rate=7	False	0.98	0.99	0.94
	True	**0.91**	**0.75**	
	avg/total	0.98	0.98	
AC-FCN	False	0.98	0.99	0.87
	True	**0.76**	**0.66**	
	avg/total	0.97	0.98	

Network Model	Classification	Recall Rate	F1-Score	AUC
U-Net	False	0.99	0.98	0.75
	True	**0.52**	**0.57**	
	avg/total	0.97	0.97	
DC-UNet dilation_rate=3	False	0.98	0.98	0.80
	True	**0.62**	**0.60**	
	avg/total	0.97	0.97	
AC-UNet atrous_rate=3	False	0.97	0.98	0.84
	True	**0.71**	**0.59**	
	avg/total	0.96	0.96	
DC-UNet dilation_rate=4	False	0.97	0.98	0.86
	True	**0.77**	**0.60**	
	avg/total	0.96	0.96	
AC-UNet atrous_rate=7	False	0.96	0.98	0.89
	True	**0.81**	**0.60**	
	avg/total	0.96	0.96	
AC-FCN	False	0.97	0.97	0.74
	True	**0.50**	**0.45**	
	avg/total	0.95	0.95	

Fig. 5 Experimental Results of Various Models on Data Block 694 and 518

We also set different coefficients at the same time to find a more appropriate degree of expansion of the convolution kernel.

Conclusions

The experimental results prove that the model proposed in this paper can obtain higher recall rate, F1 score and AUC value on the test sample, and its ROC curve is closer to the upper left corner than other models. It shows that this model is better for feature extraction of the original image, can restore the original image more fully during the upsampling process, and can detect RFI in radio observation data more comprehensively and accurately.

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