Research and Application of Recurrent Neural Network in Solar Radio Interference Filtering

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Abstract. The various interfering signals present in the space result in the inability to obtain a clean and clear solar radio dynamic spectrum, which affects the effective observation of solar radio burst events. At the data processing level, we propose a method for predicting and processing radio interference signals in solar radio burst events using recurrent neural network in deep learning. Firstly, the radio signal that satisfies the condition is selected by the amount of solar radio flux of all frequency channels at some moment, and then the position of the initial time of the burst event is located by using the variation curve of the solar radio flux with time under the single frequency channel. After that, the constructed recurrent neural network is used to predict the signal value of the radio in the burst area. Finally, according to the linear additivity of the signal, the value of the clean pure burst event is obtained by subtracting the predicted radio value from the original value of the burst area. The experimental results show that the proposed method can effectively remove the interference in the solar radio dynamic spectrum and preserve the effective information of the burst event to the greatest extent. This provides a new idea and research direction for deep learning in the anti-interference processing of astronomical big data.

1. Introduction
Reference [1] mentions that flares, prominence bursts, and coronal mass ejections (CME), which are accompanied by intense energy release, are called solar radio bursts. During the solar radio burst, the extremely enhanced solar radiation, a large number of charged high-energy particles and ejected magnetized plasma will be released in a very short time, which will become the source of the change of the electromagnetic environment in the earth space. Therefore, the observation and study of solar radio spectrum and its fine structure have important application value in space physics and synoptic meteorology.

The space observation of solar activity needs to use solar radio spectrometer. However, when the solar radio spectrometer receives solar radio signals, it will also receive all kinds of radio interference signals and other electromagnetic interference signals in space. The existence of these interference signals makes it impossible to get a clean and clear solar radio dynamic spectrum, especially some
interference signals which occupy a wide frequency band and the signal intensity is greater than the solar radio flux intensity, will cover the burst event. As a result, the observation and analysis of solar radio burst events are seriously affected.

In order to better observe the complete solar radio burst events, the interference filtering measures are divided into hardware processing and software processing. Reference [2] suppressed interference by selecting anti-interference amplifiers, filters, and so on in hardware processing, but the hardware processing method is not suitable for the built solar radio spectrometer because of the long adjustment period of circuit elements and low processing efficiency. And using this method cannot remove all kinds of interference signals. Therefore, the observation stations choose to use software to process the interference signals generally. Reference [3-6] used wavelet transform to remove interference from different burst events, and finally extracted the explosion structure. This method is mostly used to process the grayscale image of the spectrum, and there are human factors in the selection of interference signals and threshold, so it is not suitable for the filtering processing of multiple burst events. Based on the observed data of solar radio spectrometer at Zijinshan Observatory, reference [7] introduced the calibration method and gave the results, which made it possible to obtain a clear solar radio spectrum. However, the calibration of spectrometer needs a lot of historical data, and there are some errors in itself.

In recent years, deep learning methods such as reference [8-9] mentions that long-time memory network and convolution neural network have been widely used in the classification of solar radio spectrum and the recognition of burst events. For example, Reference [10] used convolution neural networks to predict solar flares; Reference [11] used long and short time memory networks to predict the total electron content of the ionosphere. In this paper, based on the software processing, through the study and analysis of the radio interference signals in the solar radio spectrum of single frequency channel, it is found that it has a certain time sequence. Therefore, the recurrent neural network in deep learning is considered to predict the radio interference signals in the burst area. According to the linear additive principle of the signal, the predicted value of the radio signals in the region are subtracted by the value of the burst region with radio interference, so as to achieve the purpose of removing the interference. The network model in this paper can train and predict radio interference signals in any frequency band and any time period. What's more, it can retain more effective information of burst events.

This not only leaves more operation space for subsequent event analysis, but also provides a new series of thoughts and directions for deep learning in the anti-interference processing of astronomical big data.

2. ALGORITHM

In this paper, the recurrent neural network (RNN) is used to process the interference signals in the solar radio, which is mainly composed of two stages: i: the network predicts the signal value of the regional radio in the burst area; ii: the value of burst area subtracts the prediction value. In the first stage, the data set is first established. After the data set is preprocessed, it enters the established network for training. Then, the network structure and the network hyper-parameters will be continuously optimized and adjusted according to the training result. Finally, the final test set enters the network for numerical prediction. In the second stage, the interference signals of the solar radio spectrum are filtered out. The interference signal processed by the RNN network is a radio signal with a wider frequency band or a signal intensity close to or even greater than the solar radio flux when the sun bursts. For some narrowband, interference signals that have weak intensity and do not have much effect on the observation of solar radio burst events are processed using conventional image filtering methods. Figure 1 shows a flow chart that filtering out interference signals in the solar spectrum.
2.1 Source of Radio Data

Unlike ordinary image processing, the method used in this paper is performed at the data level. The data selected in this paper comes from the data packets collected by the project team’s self-developed high-resolution solar radio receiver. The data is processed by FFT operation and digital polarization synthesis in the FPGA and then the cumulative operation is performed within the time-resolution. Finally, a left-lateral signal and a right-lateral signal are obtained. Since the two signals are equal-sized and opposite-direction signals, only the left-lateral signal is used for research.

The ChaShan Solar Observatory observed a solar burst event on September 9, 2017. And the quiet solar radiation value of the event is 0, that is, the background value of the image is 0. Therefore, this paper selects the solar radio burst event with radio interference signals for filter processing for a period of time. Figure 2 shows intensity of the selected burst event, with a frequency range of 180MHz-330MHz, a frequency resolution of 16KHz, and a time resolution of 10ms.

![Figure 2 The intensity map of the solar radio burst event on September 9, 2017](image)

Figure 2 The intensity map of the solar radio burst event on September 9, 2017; the abscissa is time, the ordinate indicates frequency, and the middle part of the graph indicates the amount of solar current and the signal strength of the radio. The different colors represent different values. Refer to the color scale axis on the right.

![Figure 3 The solar radio flux diagram at different frequency channels at a single moment](image)

Figure 3 The solar radio flux diagram at different frequency channels at a single moment (the moment when there is no solar radio burst); the abscissa indicates the frequency, the ordinate is the magnitude of the radio current corresponding to each frequency channel, and the ordinate is displayed in logarithm.
In Figure 2, the frequency of the radio interference signals are mainly concentrated in 240MHz-270MHz, and the high intensity of the radio signals directly cover the solar radio burst event, which affects the observation and research of the complete solar radio burst event. This paper will use the RNN method to process these radio signals. Firstly, we should plot the radio flux at all frequencies at a certain moment in Figure 2 (excluding the time of the solar radio burst event), the result is shown in Figure 3. And then define the threshold according to the magnitude of the solar radio flux of the burst event and select a frequency channel greater than the threshold (in this paper, the threshold ≥3). Finally, the value of the selected radio signal corresponding to the frequency channel is stored to establish a data set.

After selecting out the radio signals to be processed, the initial moment of the solar radio burst needs to be determined. The location of the solar radio burst is determined by the solar radio flux curve at the frequency point near the selected radio station. Taking the frequency point of 260MHz as an example, the curve of the solar radio flux of the frequency point with time is shown in Figure 4. It can be seen from the figure that the international time of solar radio burst is 6:52:23.755.3, so the data before the time is used as the training data.

2.2 Establish a Data Set

The establishment of the data set and the construction of the network are the two major components of the deep learning algorithm. In order to improve the accuracy of training and prediction results, the data needs to be pre-processed before entering the network. Although the units of the original data and the radio signals extracted in the previous section are identical, there is a span between the data, which would cause the convergence speed of the training network to be slow and the final result in not satisfactory. Therefore, this paper uses the min-max standardization method to normalize the training data and linearly transforms the data to [0, 1].

The prediction of the radio signals sequence can be understood as a regression analysis, that is, by analyzing the relationship between the values of the sequence for trend prediction. However, in reality, the radio data collected by the spectrum analyzer may be affected by external factors at a certain moment and may affect the prediction of the final result. Therefore, in the case of sufficient sample data, this paper considers segmentation of the radio sequence and artificially establishes a mapping to find the relationship between the time period and the time period.

Figure 5 is the schematic diagram of data set creation, in which $X_t$ represents the value of radio signals at the time of t. The figure contains three windows: input window, output window and segmented window. The segmented sliding window contains all the sequences of the input window and the output window, and the three windows as a whole slide on the time axis to take values. The input window and the output window contain the same number of data frames. The number of data frames is one of the network hyper-parameters and is named time_step. In addition, there is a certain time interval between the two windows. In order to preserve the relationship between adjacent sequences as much as possible and improve the accuracy of prediction, the time interval is set to 1 frame. Thus, the segment-to-segment mapping relationship is established, and the sequence values of
(t-(time_step-2)) to (t+1) are predicted according to the sequence of (t-(time_step-1)) to (t), where the sequence value at time (t+1) is the desired prediction result of radio signals sequence.

2.3 Establishment of Recurrent Neural Network

RNN introduces the concept of time by "looping" so that data is continuously accumulated on the time axis, thereby storing historical information. Figure 6 shows the traditional neural network structure diagram. In the figure, A is the module of the neural network, and $x_t$, $h_t$, $y_t$ represent the input, hidden layer state and output at the time t, respectively. $W_1$, $W_2$, $W_3$ are weight coefficient matrices between layers. It can be seen from the figure that in the process of forward data transfer, the hidden layer unit not only receives the input layer information of the current time, but also receives the information of the hidden layer unit at the previous moment, thereby realizing the memory of past time information feature.

The hidden layer output can be expressed as:

$$h_t = f(h_{t-1}, x_t)$$

Where $f(.)$ is the activation function of the hidden layer which often uses the Tanh function and the Sigmoid function. This paper chooses the latter. The network output can be expressed as:

$$y_t = g(W_3^T h_t)$$

Where $g(.)$ is the activation function of the output layer.

In theory, RNN can handle a sufficiently long time series, but the problem of gradient disappearing makes RNN actually only deal with short-term information [12]. The radio signal in this paper needs to process a long time series at one time. Therefore, we choose a special RNN structure---Long Short-Term Memory (LSTM) to predict the radio signals. The problem of gradient disappearance due to excessive number of layers is avoided by adding a "gate" of the judgment information to the module that repeatedly links in the hidden layer. Information gates are generated by sigmoid functions and are divided into input gates, forgetting gates, and output gates. The nature of the function is such that each gate message has a real parameter in the range [0,1], which represents the proportion of information passing through each gate. Figure 7 shows the internal structure of the LSTM hidden layer at a certain moment and describes the flow of the data.

The above data transfer process can be expressed by a set of formulas. The forgetting gate calculation formula is:

$$f_t = \sigma(W_f h_{t-1}, x_t, b_f)$$

The input gate calculation formula is:

$$i_t = \sigma(W_i h_{t-1}, x_t, b_i)$$

$$\tilde{c}_t = \tanh(W_c h_{t-1}, x_t, b_c)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{c}_t$$

Figure 5 Schematic diagram of data set creation
The output gate calculation formula is:

$$o_t = \sigma(W_o \cdot \hat{h}_{t-1} + x_t) + b_o$$  

$$h_t = o_t \cdot \tanh(C_t)$$  

Where $W$ refers to the weight parameter of the network, $b$ refers to the bias, $t$ represents the moment, $h$ is the hidden layer state, $x$ is the input of the network, and $C$ refers to the state of the LSTM cell. $i$, $f$, $o$ represent input gate, forgetting gate and output gate structure respectively. The activation functions of these three kinds of gates are all sigmoid functions, and the tanh function is selected when the network updates the cell state.

3. Experimental Result

This paper is ultimately make prediction of the value of the radio signals in the burst area. Because of the original value of the prediction area cannot be known in the actual burst event, the accuracy of the network prediction result cannot be verified. Therefore, this chapter first predicts the first 100 frames of radio data in the prediction area, and compares the predicted values with the corresponding original data. Then,
Figure 8 Test set prediction results (the red curve in figure a and the red scatter in figure b indicate the prediction data. The blue curve and the blue scatter indicate the original data of the radio).
Figure 9 Comparison of 240MHz and 244MHz radio signal processing results
the network structure is adjusted and optimized based on the comparison results. Figure 8(a) and (b) show the predicted result line chart and scatter plot for the test set (100 frames of radio data) of one channel of the 244MHz. From Figure 8 (a), it can be seen that the trained network can predict the changing trend of most radio signals. Although the accuracy of the prediction value in Figure 8 (b) is not particularly high, the result is not very different from the original value.

According to the network structure and network parameters of the above test results, we predict all the radio signals of burst event in this paper and then process it using the matlab software. The burst area is subtracted from the radio value predicted using the RNN method, and the non-burst area is filtered using the ordinary image processing method, that is, the average value of the frequency channel is subtracted. Figure 9 shows the original picture of the 240MHz (Fig. (a), (b), (c)) and 244MHz(Fig.(d), (e), (f)) radio signals, the ordinary image filtering results and the filtering results of this method. It can be seen from the comparison that the processing method of this paper retains more burst information, and the effect is obviously better than the ordinary image filtering method.

The result of the radio interference signal processing in the complete burst event is shown in Figure 10. It can be seen from the figure that the interference signal processing is relatively clean, and after the interference is removed, the small burst event in the red frame is clearly visible. However, the non-burst area processed by the ordinary image filtering method also has some sporadic radio interference signals,
which can reduce the display effect by reducing the time and frequency resolution. Figure 11 shows the effect of reducing the time resolution by 6 times (reduce sampling to 60ms) and reducing the frequency resolution by 16 times (reduce sampling to 0.49MHz). It can be seen that there are sporadic stations in the same color axis range. The signal is barely visible (actual value still exists), and a complete burst event is clearly displayed.

4. Conclusion
In this paper, a special recurrent neural network - LSTM network is used to predict the radio interference signal in the solar radio burst area. According to the linear additivity of the

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