Convolutional Neural Network for Classification of Solar Radio Spectrum

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Abstract-----This paper makes the first attempt to utilize convolutional neural network (CNN) for classification of solar radio spectrums. The solar radio spectrum is a two-dimensional gray-scale image with one dimension of frequency and the other of time. Taking the advantages of CNN, we can efficiently learn the distinct characteristic of different types of spectrum, and further classify them even more accurate. The proposed CNN-based network consists of four convolution layers, four pooling layers and one fully connected layer. Its input is spectrums of the size 120×120. The output gives the type of each spectrum among "burst", "non-burst" and "calibration". Experimental results demonstrate that the proposed CNN can achieve more accuracy of classification of solar radio spectrum beyond our previous efforts by employing deep belief network (DBN) and autoencoder (AE).

Keywords-----Deep learning, convolutional neural network (CNN), classification, solar radio spectrum.

I.INTRODUCTION

Solar radio astronomy is an emerging interdisciplinary field of radio astronomy and solar physics. The discovery of radio waves from the Sun provides a new window to investigate the solar atmosphere, and then new information about the Sun can be obtained. As solar radio telescopes have been improved significantly in recent years, fine structures in solar radio bursts can be detected. In this study, we use data obtained by Solar Broadband Radio Spectrometer (SBRS) of China [1] to investigate automatic classification of solar radio spectrum recurring to deep learning technique. The SBRS is characterized by high time resolution, high frequency resolution, high sensitivity, and wide frequency coverage in microwave region. It monitors solar radio bursts in the frequency range of 0.7–7.6 GHz with time resolution of 1–10ms. Five component spectrometers working on five wave bands, 0.7-1.5, 1.0-2.0, 2.6-3.8, 4.5-7.5, and 5.2-7.6 GHz, compose the SBRS. The high frequency and high time resolutions result in massive data of solar radio observation for researchers to analyze. In the observed data, burst events are rare, and always along with interference, so it seems impossible to identify whether the data containing bursts or not and figure out which type of burst it is by manual operation timely. Thus, classifying observation data automatically will be quite helpful for solar radio astronomical study.

In recent years, approaches based on deep learning [2] have proven to be state-of-the-art in many tasks, and these tasks including visual recognition [3, 4], audio recognition [5, 6] and natural language processing [7, 8]. Since these methods are able to learn useful features directly from unlabeled and labeled data to avoid the need for manual engineering, which undoubtedly gives new insight into the automatic analysis of the solar radio spectrum. Our previous papers [9, 10, 11] proposed using automatic encoder (AE) [10] and deep belief network (DBN) [9] method to learn the representation from mass of data of SBRS. For comparison, we also tried PCA for classification of spectrum by cooperating with SVM in [9]. PCA method is mainly used to find the direction of the largest variance in the data set, and represent each data point by its coordinates along each of these directions. However, the PCA cannot learn well the data representing the target task. AE is an unsupervised learning algorithm that uses back propagation to set its target value equal to the input. It tries to learn an approximation to the identity function so that the output is similar to the input. AE is very helpful for representation learning. There are also many other AE variations, such as denoising AE [12], stack AE [13] and etc. However, these AEs treat the input data equally, so that it is not possible to distinguish the characteristics of the various inputs and not to capture the differences between the different modal inputs. For the DBN, our previous work [9] has shown that it can learn the representation of solar radio spectrum well, and classify spectrum to different types better than PCA and AEs, which will be shown in Section IV.

In this paper, we try to use another deep learning method, convolution neural network (CNN), to study the representation of solar radio spectrum. We modify the pre-processing of SBRS data to adapt to the CNN. Based on the

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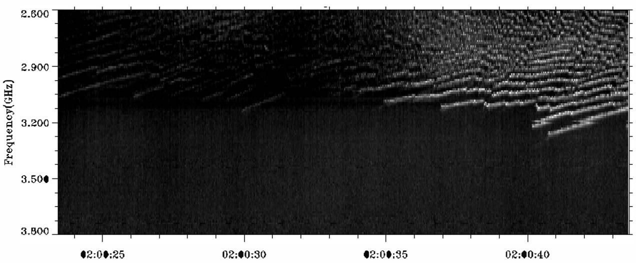
learnt representation, we can further automatically classify compare with our previous works [9, 10, 11]. The main contribution of this paper lies in that the first attempt to use the CNN learns representation of solar radio spectrum for further automatic classification.

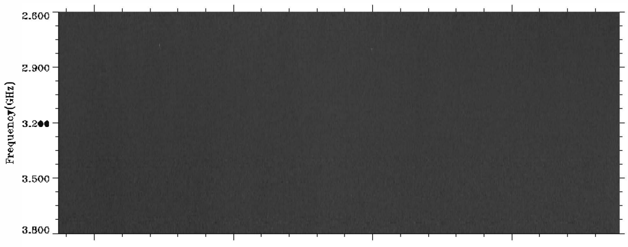
The rest of this paper is arranged as follows. Section II introduces the employed spectrum database. Section III gives the details of the proposed CNN-based network. Experimental results are provided in Section IV, and conclusions given in the last section finalize this paper.

II. SOLAR RADIO SPECTRUM DATABASE

The SBRS of China is designed to obtain dynamic spectrums of solar microwave bursts. It consists of five “component spectrometers”, which operate in five different bands. All five component spectrometers work at the same time to record solar radio radiation. The spectrum is the visualization of recorded data. It can be represented by a gray-scale image as illustrated in Fig. 1. The intensity of each pixel represents the amount of solar radio radiation at a certain frequency and at a certain time point. The whole image illustrates solar radio radiation over multiple frequency channels in a short time period. The original size of the spectrum is 120×2520. It has heavy redundancy along time axis. For saving computational complexity, it is resized into 120×120.



(a) “burst” type of spectrum



(b) “non-burst” type of spectrum Fig.

1. Solar radio spectrum of SBRS

The statistics of SBRS data show that only a very small percent of data is solar radio burst among all recorded data. Therefore, only figuring out bursts from massive data is significantly meaningful for reducing human participation in data analysis. Thus, developing automatic algorithms of solar radio spectrum into different types, and get better results spectrum classification among “burst”, “non-burst” and “calibration” was investigated in our previous efforts [9,10,11], and a database was established with these three types of spectrums and corresponding labels. The details of the established database are given in Table I. A “burst” spectrum contains at least one solar radio burst, while “non-burst” represents a spectrum that does not contain any recognizable burst. The “calibration” type refers to a specific spectrum containing calibration signal used for computing physical parameters of solar radio radiations.

TABLE I. THE DETAILS OF THE DATABASE

Spectrum types	0	1	2	total
The number of spectrums	6670	1158	988	8816

III. NETWORK FOR SOLAR RADIO SPECTRUM CLASSIFICATION

Over the past few years, deep learning has been successful in solving many problems. Among the different types of neural networks, CNN is the most in-depth study. In the early days, it was difficult to train high performance CNNs [14] without over-fitting due to lack of training data and computational power. With more labeled data and the recent development of GPU, the use of CNN has produced very good performance in many experiments. Inspired by the success of CNN on image classification, we first introduce CNN to study solar radio classification in this work. The details of the proposed CNN model are explained as follows.

CNN is composed of convolution, down-sampling and fully connected layers. The theoretical basis of the convolution layer is mainly the concept of receptive field in biology, and local receptive field and weight sharing are the common points between convolution and receptive filed, which can greatly reduce the parameters that neural network needs to train. Down-sampling, which is also named pooling, is the sub-sampling of images in fact. It is used to reduce the amount of data while still retaining useful information. By stacking the convolutions and the pooling layers, one or more fully connected layers can be formed, enabling higher-order inference capabilities.

Our proposed CNN model shown in Fig.2 consists of four pairs convolution layers and corresponding pooling layers (C1-P1, C2-P2, C3-P3 and C4-P4) followed by a fully connected layer (F1). We use spectrum of the size 120×120 after pre-processing as the input of the network. C1 contains 1×5 patch filter, the purpose of which is to extracts the local features of the input data and constructs the feature maps in layer C1. Assuming 32 convolution kernels, we obtain 32 feature maps with the size 120×120 after C1. Then, these obtained feature maps are pooled in P1. Here, we use 2×2 pooling kernel. After pooling, the 120×120 feature maps are reduced to 60×60 feature maps.

C2-P2, C3-P3 and C4-P4 have the same structure as C1-P1 in the proposed model. The number of feature maps of C2, C3, C4 are 64,128 and 256 respectively. The kernel size is 1×5 for C1-C3. Different from C1, C2 and C3, the kernel size is 1×3 for C4. After C4-P4, we can get 256 feature maps with the size of 8×8. Then, a fully-connected layer F1 with 1024 nodes is applied to output of C4-P4. Rectified unit is used as activation function, and dropout is with a probability of 0.75 in F1 to accelerate convergence and avoid excessive dependency on certain nodes. Finally, a softmax layer is stacked on the top of the network for the purpose of classification. For clearly understanding of the data flow of the whole network, we list all layers, inputs, outputs and kernel sizes in Table II.

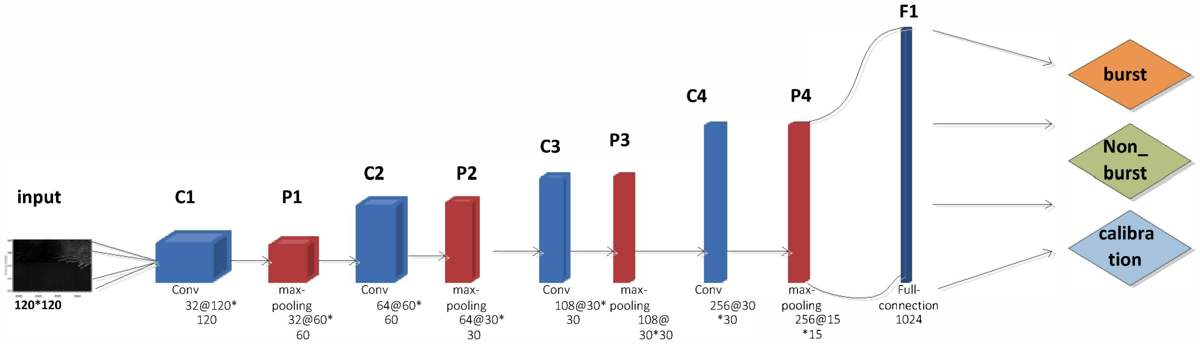


Fig. 2. The architecture of the proposed network

TABLE II: THE PARAMETERS OF CNN ARCHITECTURE

Layer	*Layer Type*	*Kernel Size (pooling region size)*	*Stride*	*Output (vector size &feature number)*
Input				(120,120,1)
C1	convolution	(1,5)	(1,1)	(120,120,32)
P1	max-pooling	(2,2)	(2,2)	(60,60,32)
C2	convolution	(1,5)	(1,1)	(60,60,64)
P2	max-pooling	(2,2)	(2,2)	(30,30,64)
C3	convolution	(1,5)	(1,1)	(30,30,128)
P3	max-pooling	(2,2)	(2,2)	(15,15,128)
C4	convolution	(1,3)	(1,1)	(15,15,256)
P4	max-pooling	(2,2)	(2,2)	(8,8,256)
F1	full-connected u			1024
Output	softmax			3

It should be pointed that we use 1×5 and 1×3 kernels instead of the conventional ones of 3×3 and 5×5 in convolution operation. The reason is that each row of the spectrum represents a frequency channel, and each channel is independent of the others. This is different from the case of general natural image, where both nearby rows and columns are highly correlated. The experiments have proved such a conclusion. The chosen strategy can improve the accuracy of classification by 2-4% over other one.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

To evaluate the proposed model on classification of solar radio spectrum, we implement it on Tensorflow library by using python. For optimization, the Adam optimizer is employed with a leaning rate of 0.01, and cost function is softmax.

Experiments are implemented on the solar radio spectrum database. Train and test sets are provided by the split of the database. The split is that 800 "burst", 800 "non-burst" and 800 "calibration" are randomly selected for training, and the rest is for testing. The detailed information about training set and test set of the split is illustrated in Table III and Table IV, respectively.

TABLE III. THE DETAILS OF TRAINNING DATA

Spectrum type	0	1	2	total
Spectrum Number	800	800	800	2400
Spectrum Size	120×120	120×120	120×120	120×120

TABLE IV. THE DETAILS OF TESTING DATA

Spectrum type	0	1	2	total
Spectrum Number	5870	358	188	6416
Spectrum Size	120×120	120×120	120×120	120×120

The accuracy of classification of the proposed model is listed in Table V. Positive rate (TPR) and false rate (FPR) are used to measure the performance. In addition, it is compared with multimodal, DBN and PCA+SVM in Table V. It can be seen that the proposed model successfully classifies the solar radio spectrums more accurate. The accuracy of classification on the database shows that not only burst but also non-burst has been greatly improved, even up to 100% on calibration. The main reason for this gain may attribute to the advantages of CNN model in image processing

To enhance the generalization ability of the networks, we increase and decrease the depth of the networks show in Table VI. The main goal of our data experiment is classification, in which burst data is the most important to us. we analyze the burst index TPR column in Table VI and can be seen, with the network layer increases, TPR value higher, (2 layer is 75.1%,3 layer is 78.2%,4 layer is 83.8%,5 layer is 84.6%,6 layer is 84.6%) which means the better the performance. However, the deeper 6 layer CNN burst TPR fail to improve and tend to be stable. It is maybe we need more data. Future, we will expand the data for further in-depth learning.

TABLE V. PERFORMANCE COMPARISION BETWEEN THE PROPOSE CNN AND PREVIOUS METHODS

	CNN		*Multimodal*		*DBN*		*PCA+SVM*	
	TPR (%)	***FPR (%)***	***TPR (%)***	***FPR (%)***	***TPR (%)***	***FPR (%)***	***TPR (%)***	***FPR (%)***
burst	83.8	9.4	70.9	15.6	67.4	13.2	52.7	2.6
non-burst	89.7	8.7	80.9	13.9	86.4	14.1	0.1	16.6
calibration	100	0.7	96.8	3.2	95.7	0.4	38.3	72.2

TABLE VI. .LAYER PERFORMANCE COMPARISON

layer	*1*		*2*		*3*		*4*		*5*	*6*
	TPR (%)	***FPR (%)***	***TPR (%)***	***FPR (%)***	***TPR (%)***	***FPR (%)***	***TPR (%)***	***FPR (%)***	***TPR (%)***	***FPR (%)***
burst	75.1	5.7	78.2	10.2	83.8	9.6	84.6	10.0	84.6	16.6
non-burst	93.7	13.7	88.1	11.3	89.7	8.7	90	8.6	82.0	8.6
calibration	99.4	0.5	100	1.4	100	0.7	100	0.3	100	1.0

V.CONCLUSIONS

In this paper, we first propose a CNN based model for classification of solar radio spectrum. Taking advantage of CNN on image classification, better performance beyond our previous efforts can be achieved. Adapted to specific image, the convolution and pooling operations are accordingly modified. We also investigate the number of layers of CNN on the performance variation of the proposed model, so that a proper scale network is selected to fit for the given dataset.

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