Spectrum Sensing Algorithm Based on LSTM and Its Implementation of Multiple USRP

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Abstract— **Aiming at the problem that the fusion rules of cooperative spectrum sensing have great impact on performance, a cooperative sensing algorithm based on LSTM, which is implemented on multiple USRPs is proposed. The received signal has different sequence characteristics when the primary user signal is present or absent. LSTM is used to extract the temporal characteristics of each primary user's signal sequence, and the fully connected layer is used to fuse the features in the fusion center, then softmax is used to classify fusion features. A number of USRPs and a host are built a spectrum sensing system, and the LSTM model obtained by offline training is used to perform online real-time detection. The system can effectively detect the primary user signal.**

I. INTRODUCTION

Spectrum sensing is an important part of cognitive radio. There are many spectrum sensing method, such as energy detection, eigenvalue detection and matching filtering, thereby determines the access time.

In order to overcome the problems of hidden terminals and shadow fading, Cooperative Spectrum Sensing (CCS) algorithm based multiple Secondary User (SU) is studied. The decision results of multiple distributed SU or data collected are fused in Fusion Center (FC) for the final decision, so the fusion method is the key of CCS. A large number of CCS algorithms, have been published, including decision fusion and data fusion (maximum ratio combining [2], equal gain fusion [3], et al). In [4], based on the energy detection algorithm, an adaptive dual-threshold spectrum sensing algorithm is proposed. The SU whose decision statistics are beyond the double threshold is fused in decision fusion, and the other SUs are fused in data fusion. Meanwhile, the detection probability is maximized by adjusting the double threshold value and the number of SU in each decision area. In [5], each SU adopts the eigenvalue detection algorithm, and two fusion methods are also used in the fusion center. For the SU between the two thresholds, the weighting factor is selected based on the Signal-to-Noise Ratio(SNR), and then the data fusion is performed. These algorithms need to design specific rules for fusion, while the reference [6] uses the energy detection method for local sensing, and uses the Convolutional Neural Networks (CNN) to fuse the sensing results of each SU in the fusion center. Performance has been improved compared to the traditional CCS algorithm. Recurrent Neural Networks (RNN) is suitable for identifying signal sequences with correlation. The reference [7] uses RNN to identify different protocol sequences and obtain good classification results. In the process of spectrum sensing, the Primary User (PU) signal sequence has correlation, which decays faster as the sequence grows, and the early information will be forgotten.

The Universal Software Radio Peripheral (USRP) can set the digital baseband and intermediate frequency parameters of wireless communication flexibly, which can be conveniently used to study the performance of the spectrum sensing algorithm on the received air interface signal. In [8], it uses CNN to perform non-cooperative offline spectrum sensing of USRP received signals.

In this paper, we propose and implement a novel cooperative spectrum sensing algorithm on multiple USRPs which is based on Long Short-Term Memory (LSTM). The contributions of this paper can be summarized as follows.

1) We propose a LSTM-based cooperative spectrum sensing algorithm. The LSTM is used in each SU to extract temporal characteristics of the received signal sequence. Due to the different environments of the SUs, their temporal characteristics have different effects on the final decision. Therefore, the fusion center uses two fully connected layers to fuse the temporal characteristics to make the final decision.
2) Several USRPs are used to build a spectrum sensing system, and the real-time sensing performance of the cooperative spectrum sensing algorithm based on LSTM in real environment is analyzed. USRP is used to collect real signals and build training and test datasets that are used to train the models offline. Finally, GNU Radio and trained models are used for real-time online cooperative spectrum sensing.
3) Through simulation, we confirm that the proposed algorithm has a better performance than other schemes. Moreover, the algorithm has been successfully implemented in USRPs, and shows some anti-frequency offset characteristics.

The remainder of this paper is organized as follows. In Section II, we introduce the system model and the proposed LSTM-base CCS scheme. In Section III and Section IV, We analyze the simulation performance of the algorithm and the performance of USRPs implementation respectively, and Section V concludes the paper.

II. SYSTEM MODEL

A. Cooperative Spectrum Sensing Model

In the following section, we consider a cognitive network that include N SU nodes, one PU node and one FC node. Each SU uses the method $\Theta(\bullet)$ to perform local signal feature extraction on the received signal. And the FC uses the method $\Psi(\bullet)$ to fuse the features extracted by the SU. Therefore, the binary hypothesis test of the existence state of PU can be expressed as:

$$Y=\begin{cases}\Psi(\Theta(\boldsymbol{v}_1),...,\Theta(\boldsymbol{v}_N)) & H_0\\ \Psi(\Theta(\boldsymbol{h}_1\boldsymbol{x}_{\mathrm{PU}}+\boldsymbol{v}_1),...,\Theta(\boldsymbol{h}_N\boldsymbol{x}_{\mathrm{PU}}+\boldsymbol{v}_N)) & H_1\end{cases} \quad (1)$$

Where H_0 and H_1 represent hypotheses that the primary user absent and present, $\boldsymbol{x}_{\mathrm{PU}}$ represents the signal transmitted by the PU node, h_i represents the channel coefficient between the PU and the i-th SU, and $\boldsymbol{v}_i$ represents the received noise. Let $\boldsymbol{y}_i$ denote the signal received by the i-th SU node:

$$\boldsymbol{y}_i=[\,y_i(1),y_i(2),\ldots,y_i(n)] \quad (2)$$

Where n represents the length of the received signal sequence. When there is a primary user signal, the received signal of the SU is $\boldsymbol{y}_i=\boldsymbol{h}_i\boldsymbol{x}_{\mathrm{PU}}+\boldsymbol{v}_i$. When it is not present, the received signal is $\boldsymbol{y}_i=\boldsymbol{v}_i$.

B. Decision Model Based on LSTM

LSTM is an improved unit of RNN, one of which is shown in Fig. 1. It has a hidden layer h_t and three gate control units, including a forgotten gate f_t, an input gate i_t and an output gate o_t. The input gate can determine how much input information enters the current unit, the forgotten gate can determine how much information the previous memory vector C_{t-1} should forget, and the output gate can determine what information the current unit will provide.

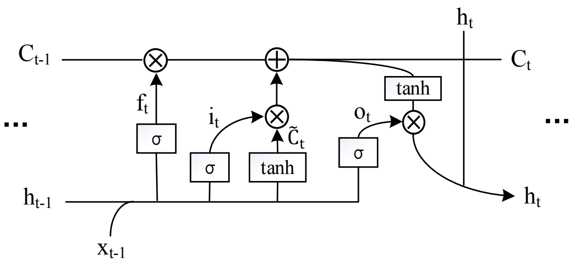

Fig. 1 LSTM Neural Unit

Each LSTM unit consists of multiple neural units whose calculation equations are defined as follows:

$$\begin{cases}\boldsymbol{f}_t=\sigma\left(\boldsymbol{W}_f[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_f\right)\\ \boldsymbol{i}_t=\sigma\left(\boldsymbol{W}_i[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_i\right)\\ \tilde{\boldsymbol{C}}_t=\tanh\left(\boldsymbol{W}_c[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_c\right)\\ \boldsymbol{C}_t=\boldsymbol{f}_t*\boldsymbol{C}_{t-1}+\boldsymbol{i}_t*\tilde{\boldsymbol{C}}_t\\ \boldsymbol{o}_t=\sigma\left(\boldsymbol{W}_o[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_o\right)\\ \boldsymbol{h}_t=\boldsymbol{o}_t*\tanh(\boldsymbol{C}_t)\end{cases} \quad (3)$$

The cooperative spectrum sensing network model based on LSTM is shown in Fig. 2.

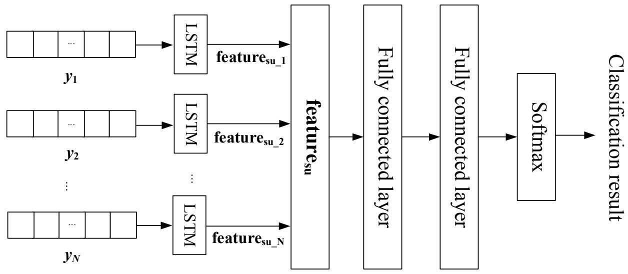

Fig. 2 Cooperative Spectrum Sensing Model Based on LSTM

The $\mathbf{feature_{su\_i}}$ represents feature eigenvector of the i-th SU, combined feature sequence is obtained in the FC as follows:

$$\mathbf{feature_{su}}=[\mathbf{feature_{su\_1}},\ \mathbf{feature_{su\_2}},\ \ldots,\ \mathbf{feature_{su\_i}}]$$

Each dimension feature has different effects on the final decision result. Therefore, multiple fully connected layers are added to the combinatorial feature sequences, and the back-propagation and gradient descent algorithms are used to adjust the connection weight parameters, which can fuse the features of all dimensions in the process of training.

The final classification layer uses the Softmax function that output form is a two-dimensional probability vector $[a, b]^T$. Ideally, $[0,1]^T$ indicates the presence of the primary user and $[1,0]^T$ indicates that the primary user does not exist. In fact, the values of a and b are not 0 or 1, but two real numbers between 0 and 1. Err represents the Euclidean distance between the output and $[0,1]^T$, which expressed as follows:

$$err=\sqrt{(a-0)^2+(b-1)^2} \quad (4)$$

The err_{th} represents error threshold, which is set to ensure that the Probability of Detection (P_d) is greatly increased in the case of a low Probability of False Alarm (P_f). It is determined that there is a primary user when the err is smaller than the err_{th}, otherwise the primary user does not exist.

C. Spectrum Sensing System Built by Multi USRPs

In order to verify the sensing performance of the proposed method in this paper, a cooperative sensing system was built using GNU Radio and USRP. GNU Radio is an open source framework that provides a lot of signal processing modules for implementing Software Defined Radio (SDR).

The cooperative sensing hardware system consists of one host and three USRPs. The host GPU uses GeForce GTX 1080 with four Gigabit ethernet cards, and the USRP X310 works with SBX-120 daughter boards. Fig. 3 shows the hardware block diagram of the actual cooperative spectrum sensing system.

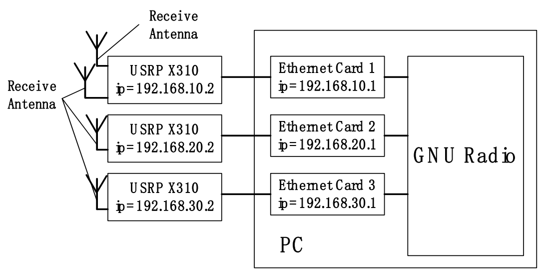

Fig. 3 Cooperative Spectrum Sensing Hardware System

Each USRP is connected to the host through the corresponding ethernet card, and their Internet Protocol (IP) address is set under the same network segment. The USRP uses the daughter board to downconvert the Radio Frequency (RF) signal to the Intermediate frequency (IF) signal, and then downconverts the IF signal to the digital baseband signal through the FPGA of the motherboard, and finally transmits baseband signal data to the PC host through the Ethernet port. The USRP hardware driver (UHD) interface of GNU Radio is used to receive the signal sequence collected by USRP in the PC host for cooperative spectrum sensing.

In order to obtain data in real time for spectrum sensing, the transceiver system is built using GRC (GNU Radio Companion). The flow diagram of the system is shown in Fig. 4.

The upper path of Figure 4 is the signal transmission flow diagram of USRP. The transmitted signal is a QPSK signal with a sampling point of 4 per symbol, a roll-off factor of 0.5, and a sampling rate of 2 MHz. Then the QPSK signal which was up-converted to a center frequency of 1 GHz is transmitted through a TX antenna. The lower three paths are the signal reception flow diagram of the USRP. The three USRPs downconvert the center frequency 1 GHz signal to the digital baseband signal and transmit the baseband signal to the GRC's Vector Sink block through the Gigabit Ethernet port. A function of dataset generation is added to the source code which is generated from Fig. 4, and the baseband signals received from the three USRPs are used to form the training and test dataset.

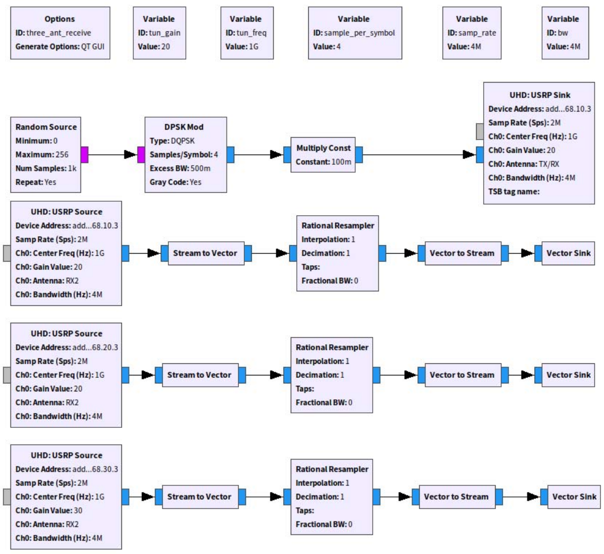

Fig.4 USRP transceiver flow diagram built in GRC

The cooperation spectrum sensing model that shows in Fig. 2 is built with the scikit-learn library and the Keras framework, therefore the procedure of training can be accelerated by CUDA and cuDNN. The training dataset is used to train the model parameters, which are saved for online spectrum sensing. Since the actual signal transmission environment may change, training is resumed at regular intervals.

III. SIMULATION AND ANALYSIS

A. Influence of Network Parameters

This section analyzes the influence of the number of memory cells unit_num of LSTM, the number of fully connected layer neurons of FC, and the number of training epoch_num on spectrum sensing performance. The dataset, which generates 1000 pairs of signal data with 10, 20 and 40 SUs receiving signal to noise ratios of -20dB~-1dB, is generated by Matlab.

Table 1 shows the P_d and the P_f obtained when the number of different memory units and the number of connected neurons are selected. P_f and P_d are the average of 1000 test results using the signal data set of 10 SUs.

It can be seen from Table 1 that with the increase of the dense_num, the trend of change of P_d is unstable, when the units_num of the LSTM is 20; The P_d gradually decreases with the increase of the density_num when the units_num is 25 and 30. And when the dense_num is not greater than 10, the P_d is higher than the P_d with units_num of 20. Therefore, the simulation below selects units_num as 30 and dense_num as 10, considering the value of P_d and P_f comprehensively.

Table 1 Influence of network parameters on sensing performance.

unit_num		**20**		**25**		**30**	
probability		P_d	P_f	P_d	P_f	P_d	P_f
dense_num	5	0.623	0.025	0.806	0.111	0.797	0.095
	10	0.586	0.024	0.687	0.056	0.790	0.091
	15	0.623	0.038	0.582	0.031	0.589	0.032
	20	0.622	0.037	0.541	0.025	0.584	0.028
	25	0.530	0.022	0.493	0.021	0.514	0.022
	30	0.566	0.021	0.488	0.018	0.489	0.017

Figure 5 shows the relationship between the P_d of the training model and the number of training when the number of SUs is 10, 20, and 40.

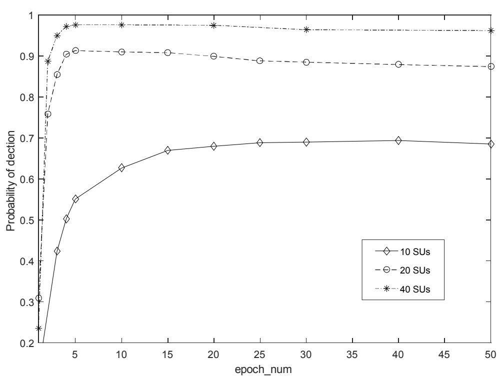

Fig.5. Convergence curve of P_d of the model

It can be seen from Fig. 5 that when the number of SUs is 10, 20, and 40, and the epoch_num is about 15, 5, and 4, the P_d of the trained models reach a convergence state. Therefore, for the number of SUs of 10, 20, and 40, the number of trainings selected is 15, 5, and 4, respectively.

B. Comparison of Algorithm Performance

In this section, we compare the performance between the LSTM-based cooperative sensing algorithm (named LSTM algorithm), the energy-detected dual-threshold cooperative sensing method (named ED algorithm) [10] , the cooperative sensing algorithm based on the difference between the maximum and minimum eigenvalues (named DMM algorithm) [11], and CNN-based cooperative sensing algorithm(named CNN algrithm).

We have trained LSTM-based and CNN-based cooperative sensing models respectively for the same datasets with the SUs of 10, 20 and 40 and the SNR of -20~-1dB.

We adjust the err of LSTM and CNN algorithm through multiple tests to make the P_f reach 0.1, and calculate the detection threshold of the ED algorithm and the DMM algorithm directly when the P_f is 0.1. The relationship curves between the P_d and the SNR of the four algorithms when the number of SU is 10, 20 and 40 and P_f=0.1 are shown in Fig. 6.

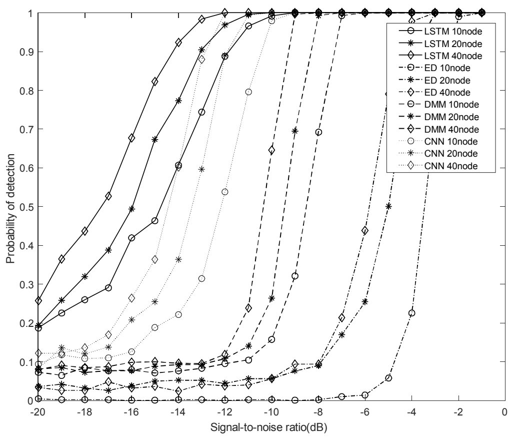

Fig.6. P_d of four algorithms under different SNR

From Fig. 6 we can see that the performance of the LSTM algorithm is better than that of the other three algorithms. When the number of SU is 40 and the SNR is -12 dB, the P_d of LSTM reaches 1, while the P_d of ED and DMM is less than 0.10. When the number of SU is 20 and the SNR is -11 dB, the P_d of LSTM reaches 1, while the P_d of DMM and ED are 0.14 and 0.04, respectively. When the number of SU is 10 and the SNR is -10 dB, the P_d of LSTM reaches 1, while the P_d of DMM and ED are 0.16 and 0.00, respectively.

When the SNR is -13dB, the Receiver Operating Characteristic (ROC) curve of the four algorithms are shown in Fig. 7.

As can be seen from Fig.7, the performance of the LSTM algorithm is significantly better than that of the three comparison algorithms. When the SNR is -13dB, the P_f is 0.20, and the number of SU is 10, 20, and 40, the P_d of the LSTM algorithm is about 0.88, 0.94, and 0.99, the CNN algorithm is about 0.49, 0.72, 0.92, while the P_d of the other two comparison algorithms is less than 0.50.

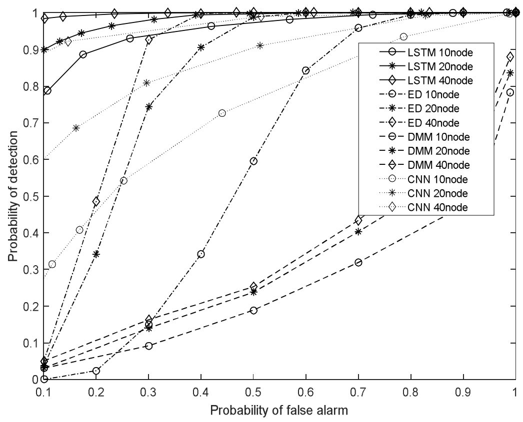

Fig.7. ROC curves of the four algorithms

IV. PERFORMANCE ANALYSIS OF HARDWARE SYSTEM

A. Offline Training

We use the hardware and software platform built in Section 2.3 for cooperative spectrum sensing. The QPSK signal transmitted by the transmitter has a bandwidth of 1.5MHz and the transmit gain expressed by $Gain_{tx}$ and the receive gain expressed by $Gain_{rx}$ are all set to 10dB. Each receiving end receives 1000 sets of signal sequences with frame length of 200 as positive samples. Then, without changing the receiving center frequency of the receiving end, the transmitting end is tuned to 400MHz to receive 1000 sets of negative sample sequences with frame length of 200. Finally, the above 2000 sets of positive and negative samples are combined into a training set.

The training parameters units_num, dense_num, and epoch_num of LSTM are set to 30, 10, and 40, respectively. Then the offline model of LSTM is trained by using the training set data.

B. Performance of Real-time Detection

The experimental parameters are the same as those in Section 4.1. Since the prior information of the environmental noise is unknown, the USRP cannot be used to set an accurate SNR for the signal. Therefore, we change the received SNR of each USRP receiver indirectly by adjusting the USRP's $Gain_{tx}$ and $Gain_{rx}$. The LSTM model obtained in Section 4.1 is used to detect 1000 cases of the presence of the primary user signal and the absence of the primary user signal. The detection probability of the real-time received signal under different antenna gain which is expressed as Gain($Gain=Gain_{tx}+Gain_{rx}$) is shown in Fig. 8.

As can be seen from Fig. 8, with the increase of Gain, the detection probability of the sensing system increases gradually. When Gain reaches 16dB, the probability of detection is 1.

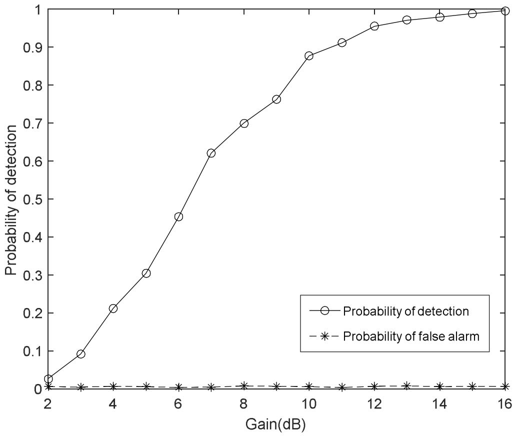

Fig. 8 Probability of detection of the hardware sensing system

The center frequency of the transmitter remains unchanged at 1GHz, and the Gain of the antenna is 16dB. The center frequency of the receiver is adjusted from 1~ 1.001GHz to receive signals, and the corresponding detection probability curve is shown in Fig. 9.

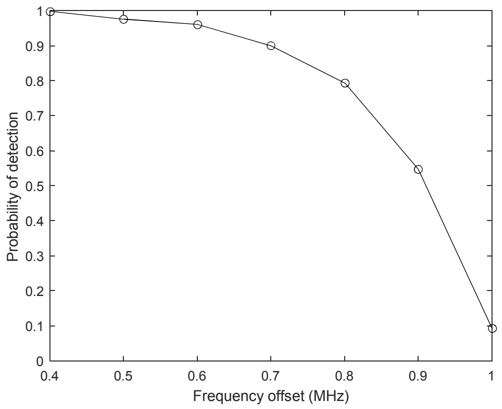

Fig.9. Anti-frequency offset performance of the hardware sensing system

As shown in Fig. 9, when the center frequency is shifted by 1 MHz, the detection probability is about 0.10, and as the offset decreases, the detection probability increases accordingly. When the frequency shift is less than 0.4 MHz, the detection probability reaches 1. Therefore, the proposed algorithm has a certain anti-frequency offset performance in the actual signal detection process.

V. CONCLUSION

In this paper, each secondary user node uses LSTM to extract the temporal characteristics of the received signal, and the fusion center uses two fully connected layers to fuse all temporal features to obtain the final decision result. The simulation results show that the proposed algorithm has higher detection performance than CNN, ED and DMM algorithms, and still has higher detection probability in the case of low SNR. In addition, the cooperative spectrum sensing system is built by three USRPs and the detection performance of the algorithm is verified. And the algorithm has certain anti-frequency offset performance.

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