Unauthorized broadcast signal recognition based on deep learning

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Abstract—**Unauthorized broadcasting is a kind of broadcasting without government approval. Its existence and spread seriously affect social security and stability. The existing unauthorized signal recognition methods are complicated in operation, large in calculation and low in recognition accuracy. In this paper, an unauthorized signal recognition method based on deep learning is proposed, which can achieve a high recognition accuracy rate while reducing the participation of personnel. The experiment has proved the effectiveness and reliability of this method.**

Keywords-component; Unauthorized broadcasting; Feature extraction; Deep learning; Signal recognition Introduction

I. BACKGROUD

Unauthorized broadcasting is the act of setting up and using the broadcasting frequency to publicize to the society without the approval of the relevant regulatory authorities. Unauthorized broadcast signals can be roughly divided into two categories: The first is the signal that does not occupy the authorized frequency point for transmission, that is, the unauthorized signal of the unauthorized frequency point; The second is the signal transmitted when the authorized frequency point overrides the authorized broadcast, or when the authorized broadcast is at rest, that is, the unauthorized signal of the authorized frequency point. The so-called "frequency point" in this paper actually refers to the frequency band centering on the frequency point. In addition the unauthorized frequency point is the frequency point other than the authorized frequency point that is within 88-108MHz (only considering FM broadcasting).

Some research work related to unauthorized broadcast recognition is reported in the literature, which mainly includes the method of feature extraction and signal classification, and the method of spectrum data analysis and processing based on multi-attribute decision scheme[1]. In the literature **[2]**, square bispectrum and kernel principal element analysis algorithm are adopted to extract the characteristic information of signals, and specific discriminant functions are used to classify signals[2]. Literature **[3]** extracts effective frequency-domain characteristics of signals, and classifies them with support vector machines[3]. Literature **[4]** used cooperative characterization classifier to classify the envelope characteristic of transient signal. However, useful features may be discarded while using the above methods for feature extraction, resulting in a decrease in the estimation accuracy. Neural network classification methods have also been reported in the literature, but these methods either classify signals at a single frequency point[5] without considering the timing of broadcast signals, or locate unauthorized stations according to signal strength[6], without focusing on the classification and recognition of unauthorized signals. In the literature **[7]**, automatic detection of abnormal signals is realized through LabVIEW, which compares the amplitude of received signals with the historical mean value, and it is considered as unauthorized signals when the difference value exceeds a certain threshold. However, the method in this paper requires a large amount of historical data and cannot distinguish the situation when the two signal powers are similar.

Aiming at the mentioned problems and based on deep learning and big data technology, this paper proposes a method of classifying and recognizing unauthorized broadcast signals based on Recurrent Neural Network (RNN), that is, Long-Short Term Memory (LSTM). Under the condition of sufficient training samples, this paper can identify the unauthorized signals with high speed and accuracy, which is helpful for the radio management department to monitor and manage the radio.

II. INTRODUCTION TO RNN AND LSTM-RNN

A. RNN

Artificial neural network can analyze and process the input data by imitating the structure and function of human brain. The BP neural network transmits the input samples forward to the output layer to obtain the output result. When the output result is different from the expected one, the error propagates back to each layer so as to update the weight value to achieve the optimal effect.

Compared with BP neural network, RNN can make historical data act on current output and conducts training through Back-Propagation Through Time (BPTT) algorithm. When the input is sequential data, the current output is related both to the current input and to the previous input. Radio broadcast signals are related to transmitting equipment. Also, they have a strong correlation in time. Ignoring the correlation in time may be greatly affected accuracy of signal classification and recognition. RNN can take the timing of radio signals into consideration by using the hidden layer, so it can make up for the defects of BP neural network.

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B. LSTM

In order to solve the gradient disappearance problem, LSTM added a "gate" structure. Figure 1 shows the internal structure of LSTM neural network, wherein, $\mathbf{S}_t$ is the cell unit at time *t*, and each cell is composed of three "gates", which are forgetting gate, input gate and output gate in order from left to right.

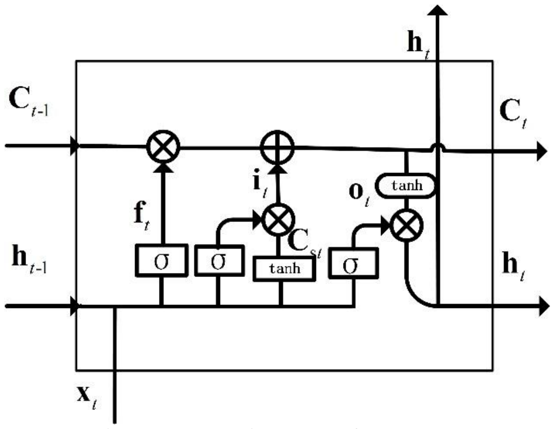

Figure 1. Internal structure of LSTM.

The forgetting gate can be expressed by formula (1), wherein, $\mathbf{f}_t$ represents the forgetting gate, $\mathbf{x}_t$ is the time series at time *t*, $\mathbf{h}_{t-1}$ is the output at time $t-1$, $\mathbf{C}_t$ and $\mathbf{C}_{t-1}$ are the cell state at time t and time $t-1$ respectively. $\mathbf{W}_f$ Is the corresponding weight coefficient, $\mathbf{b}_f$ is the corresponding bias. The physical meaning of equation (1) is: connecting $\mathbf{x}_t$ and $\mathbf{h}_{t-1}$ head to tail, obtaining the vector between 0 and 1 through the sigmoid function, and making it multiply $\mathbf{C}_{t-1}$ to determine how much of the cell state $\mathbf{C}_{t-1}$ remains in the $\mathbf{C}_t$. 0 means all abandoned, 1 means all retained.

$$\mathbf{f}_t = \sigma\left(\mathbf{W}_f \cdot \left[\mathbf{h}_{t-1}, \mathbf{x}_t\right] + \mathbf{b}_f\right) \tag{1}$$

The input gate can be expressed in formula (2)—(4), wherein, $\mathbf{i}_t$ is the input gate, $\mathbf{W}_i$ and $\mathbf{W}_C$ are the corresponding weight coefficients, $\mathbf{b}_i$ and $\mathbf{b}_C$ are the corresponding biases. Their meanings are: connecting $\mathbf{x}_t$ and $\mathbf{h}_{t-1}$ head to tail, and sending them into the sigmoid and tanh layers. Tanh is used to generate candidates for updated values $\mathbf{C}_{st}$. The output through tanh is in [−1 , 1], indicating that the cell state needs to be strengthened in some dimensions and weakened in some dimensions. The output of the sigmoid layer (input gate layer) is multiplied by the output of the tanh layer, which acts as a scaling function. In extreme cases, sigmoid output 0 indicates that the cell state on the corresponding dimension does not need to be updated. Finally, adding the part processed by the forgetting gate determines how much the input $\mathbf{x}_t$ is saved to the cell state $\mathbf{C}_t$.

$$\mathbf{i}_t = \sigma\left(\mathbf{W}_i \cdot \left[\mathbf{h}_{t-1}, \mathbf{x}_t\right] + \mathbf{b}_i\right) \tag{2}$$

$$\mathbf{C}_{st} = \tanh\left(\mathbf{W}_C \cdot \left[\mathbf{h}_{t-1}, \mathbf{x}_t\right] + \mathbf{b}_C\right) \tag{3}$$

$$\mathbf{C}_t = \mathbf{f}_t \cdot \mathbf{C}_{t-1} + \mathbf{i}_t \cdot \mathbf{C}_{st} \tag{4}$$

The output gate can be expressed in formula (5) and (6), wherein, $\mathbf{o}_t$ is the output gate, $\mathbf{h}_t$ is the output of the current cell, $\mathbf{W}_o$ is the corresponding weight coefficient, $\mathbf{b}_o$ is the corresponding bias. Their meanings are: sending the state of the cell to a tanh function to obtain a candidate for the output value. Which parts of the candidate will eventually be output is determined by a sigmoid layer, that is, the output gate is used to control how much of the cell state $\mathbf{C}_t$ remains in the output $\mathbf{h}_t$ of LSTM.

$$\mathbf{o}_t = \sigma\left(\mathbf{W}_o \cdot \left[\mathbf{h}_{t-1}, \mathbf{x}_t\right] + \mathbf{b}_o\right) \tag{5}$$

$$\mathbf{h}_t = \mathbf{o}_t \cdot \tanh\left(\mathbf{C}_t\right) \tag{6}$$

III. STUDYING MODEL

The LSTM neural network is used to construct the signal classification and recognition model, which consists of the following three steps: data collection, frequency point database comparison and pre-classification, and LSTM classification.

A. Data Collection

In order to fully and accurately identify unauthorized signals, three types of signals should be collected: ① Authorization signal at authorization frequency point, ② Unauthorized signal at authorized frequency, ③Unauthorized signal at unauthorized frequency point. What we choose the signal acquisition device is USRP + LabVIEW.

TABLE I. DATA COLLECTION STATISTICAL TABLE

Frequency points （MHz）	87.6	89.1	90.6	93.1	95.6	99.1	100.8	103.3	105.7	106.7	107.8
Group 1	√	√	√	√		√	√		√	√	
Group 2	√	√	√				√	√	√	√	√
Group 3	√	√		√			√	√	√	√	√
Group 4	√	√		√	√	√	√		√	√	
Group 5		√		√	√		√	√	√	√	√
Group 6	√	√	√	√	√	√	√		√		
Group 7		√	√	√	√	√	√		√	√	

LabVIEW is a graphical programming system, which provides many controls similar in appearance to traditional instruments (such as oscilloscope and multimeter) to make it more convenient for users to operate. As a general peripheral of software radio, USRP can collect and receive radio signals by using the software package provided by LabVIEW. In this paper, LabVIEW and USRP are combined to realize the transceiver function of FM broadcasting. TABLE I shows the collection of authorized broadcast signals at authorized frequency points. The collection of unauthorized signals at each group of authorized frequency points is the same as that in TABLE I.

B. PRE-CLASSIFICATION

The pre-classification process of the frequency point database is shown in figure 2: first, the frequency point database is made from the frequency point information saved during the collection of authorized broadcast signals, and the last line of the classified test sample is respectively compared with the frequency point database. If a frequency point cannot find the corresponding information in the frequency point database, then the signal of the frequency point is judged the unauthorized signal of the unauthorized frequency point, which is determined to be a class of unauthorized signal. After the frequency point comparison in the classification test sample is completed, the unauthorized frequency point data in the sample is removed and a new classification test sample is generated. At this time, the test sample only contains the authorized data of authorized frequency point and the unauthorized data of authorized frequency point.

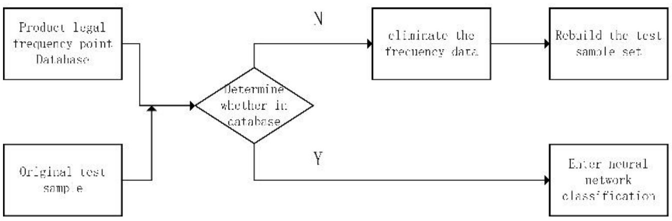

Figure 2. The pre-classification process

C. Signal Classification Based on LSTM

1) The training process

The building and training of LSTM are conducted under Tensorflow, implemented by the Python. In order to prevent the occurrence of overfitting phenomenon, this paper uses the method of Dropout, in the process of neural network training, making the ratio 0.5 to discard some data. In addition, in order to obtain better training effect, the sample size of each minbatch is one tenth of the total sample number and the minibatch cycle is 100 times each time. After sending the training sample into LSTM, the relationship between the number of training and each minibatch training accuracy can be shown in Figure 3. As can be seen from the figure 3, the network soon tends to be convergent, and with the increase of the training number, the accuracy rate will be higher and higher until approaching to 1.0.

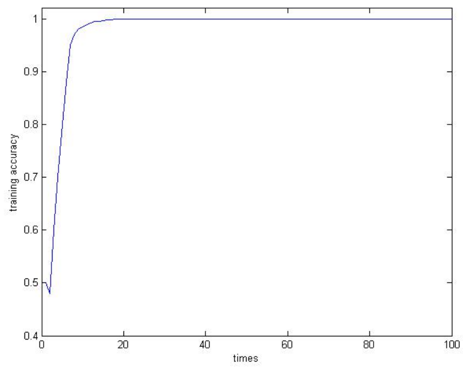

Figure 3. The relationship between the number of training and training accuracy

2) The testing process

The output of LSTM is a prediction matrix, so it needs to be processed, that is, each row of the prediction matrix is compared to obtain the index of the maximum value of each row. Since this paper is a binary classification problem, the index value returned is 0 or 1.1 means that the predictive value of the data segment is "authorized signal at authorized frequency", and 0 means that the predictive value of the data segment is "authorized signal at authorized frequency", that is, another kind of unauthorized signal.

Since the network structure is the main factor that affects the accuracy of neural network, the influence of LSTM on the accuracy of classification and recognition is explored from the number of network nodes and hidden layers.

Experiment 1: In this experiment, the number of hidden layers is 3, and the learning rate is set as 0.01. As can be seen from the figure 4, when the node number is 4, the test accuracy rate is only 88%, and with the increase of node number, the test accuracy rate will increase accordingly. And when the number of nodes exceeds 128, increasing the number of nodes will not greatly affect the test accuracy, but will lead to the increase of training time.

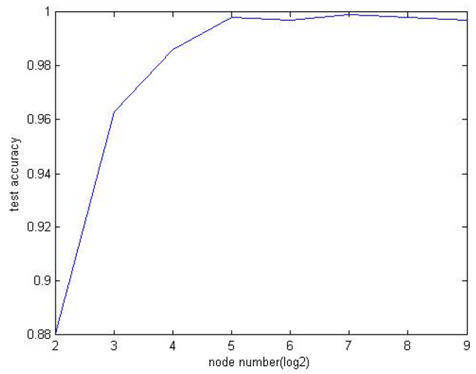

Figure 4. The relationship between test accuracy and network nodes

Experiment 2: In this experiment, the network nodes are 3, and the learning rate is set as 0.01. As can be seen from the figure 5, when the number of hidden layers is 1, the test accuracy is 99.1%, and when the number of hidden layers is increased, the test accuracy will be increased accordingly.

However, as the test accuracy is already high, when the number of hidden layers reaches 3, more layers will not significantly improve the test accuracy.

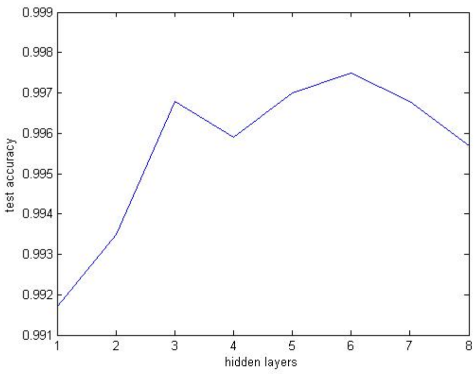

Figure 5. The relationship between the test accuracy and the number of hidden layers

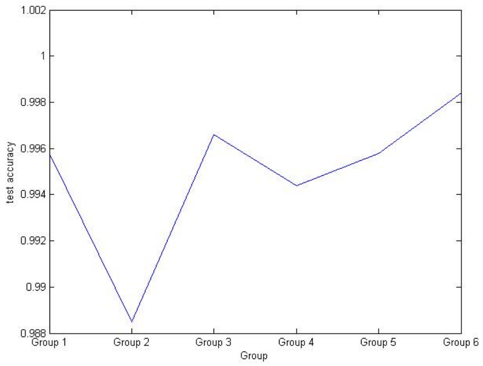

Figure 6. Accuracy chart of each group test

Therefore, when the six groups of test samples were sent into the neural network for testing, the learning rate was set at 0.01, the number of network nodes was set at 256, and the number of hidden layers was set at 3. The test accuracy of each group was shown in figure 6.

As can be seen from the figure 6, the accuracy rate of the six groups of test data is higher than 98.8%, indicating that this method can accurately and effectively identify and classify unauthorized signals.

Since the signal is segmented during sample production, if the prediction results of the corresponding data segments of each frequency point are processed before the test accuracy, the accuracy of classification and recognition can be further improved. The processing process is as follows:

a) Each row of the prediction matrix is compared to obtain the index of the maximum value of each row. Since this paper is a binary classification problem, the index value returned is 0 or 1;

b) Determining whether there are more zeroes or more ones in the multiple predictions for each frequency point;

c) If the number of 0 is more than the number of 1, setting the prediction label of the frequency point to (0, 1); otherwise, setting it to (1, 0);

d) Outputting forecast label, realizing the binary classification. When the prediction label is set to (1, 0), the output result is "authorized signal of authorized frequency point". And when the prediction label is set to (0, 1), the output result is "unauthorized signal of authorized frequency point", namely another kind of unauthorized signal;

e) The estimated accuracy is obtained by comparing the predicted tag value with the actual tag value.

TABLE II. TEST RESULTS

Frequency points（MHz）	87.6	89.1	90.6	100.8	103.3	105.7	106.7	107.8
Total data segments	1000	1000	1000	1000	1000	1000	1000	1000
Correct segments	935	1000	1000	987	999	997	996	999
Wrong segments	65	0	0	13	1	3	4	1
Uncorrected frequency point accuracy（%）	93.5	100	100	98.7	99.9	99.7	99.6	99.9
Corrected frequency point accuracy（%）	100	100	100	100	100	100	100	100
Total correct rate Acc（%）	100							

A set of test data is presented in TABLE II of the test results. Each group of data contains 8 authorized frequency signal and eight authorized frequency point of unauthorized signals, a total of 16 signals. Each signal contains 500,000 data points, and since each signal is divided into 500 data segment, so each frequency point contains 1000 data segment. The uncorrected frequency accuracy can be obtained through the neural network and only through the processing of step *a)*. The modified frequency accuracy obtained after steps *b)-d)* can reach 100%, and the total correct rate of Acc is also at 100%. Total accuracy Acc is calculated by formula (7), where Sum is the number of total frequency points and Wro is the number of estimated wrong frequency points. The calculation rule of Wro is: when the number of predicted wrong data segments at a certain frequency point reaches more than half of the total number of segments, indicating that the data at the frequency point has made a wrong predicted:

$$\text{Acc}=\frac{\text{Sum}-\text{Wro}}{\text{Sum}} \tag{7}$$

As can be seen from TABLE II, although the accuracy of uncorrected frequency points in some data segments is low in the test process, the accuracy of classification can be improved after the processing in steps *b)-d)*, and the classification results can be more consistent with the actual situation.

Furthermore, the collected data of each group were tested. A total of 144 signal data (including 48 authorized signals, 48 unauthorized signals of authorized frequency points and 48 unauthorized signals of unauthorized frequency points). Although some data segments can still be predicted incorrectly, the test accuracy can reach 100% after the steps *b)-d)* processing.

IV. Conclusion

Based on the pre-classification of frequency point database for the collected signals, this paper adopts the deep learning theory and method to obtain the prediction results of LSTM, and then carries out data processing on the prediction results to realize the classification and identification of unauthorized broadcast signals. The experiment shows that the comparison of frequency point database and LSTM for unauthorized classification can reduce the computational complexity and obtain a high classification accuracy rate.

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