Spectrum Prediction in Cognitive Radio Based on Sequence to Sequence Neural Network

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Abstract. Cognitive radio provides the ability to access the spectrum that is not used by primary users in an opportunistic manner, enabling dynamic spectrum access technology and improving spectrum utilization. The spectrum prediction plays an important role in key technologies such as spectrum sensing, spectrum decision, spectrum sharing and spectrum mobility in cognitive radio. In this paper, aiming at the spectrum prediction problem in cognitive radio, a spectrum prediction technique based on the sequence to sequence (seq-to-seq) network model constructed by the GRU basic network module is proposed. Due to the long and short time memory function of the GRU network structure, its performance is better than the previous Multi-Layer Perception (MLP) network model. This paper also explores in depth the impact of changes in the length of the input sequence on the prediction results. And the proposed seq-to-seq network model also performs well for multi-slot prediction and multi-channel joint prediction.

Keywords: Cognitive radio · Spectrum prediction · Sequence to sequence network model

1 Introduction

With the development of communication technologies, the proliferation of mobile devices has led to a shortage of spectrum resources. In the past, the static spectrum allocation strategy has low spectrum utilization and cannot meet the frequency requirement. What new communication systems mainly focused on is

G. Gui and L. Yun (Eds.): ADHIP 2019, LNICST 302, pp. 343–354, 2019.
https://doi.org/10.1007/978-3-030-36405-2_34

how to improve spectrum utilization without reducing the quality of service. The advent of software radios has providing dynamic reconfiguration of devices. In the 1990s, the emergence of software-based radios and the maturity of machine learning techniques led to cognitive radios (CR), which is a technology for intelligent analysis of the spectrum environment that provides reliable communication and efficient use of the radio spectrum. Through the sense of the spectrum environment and adaptive learning from the surrounding environment, CR will allocate the idle spectrum in certain space and time to unauthorized users, thereby achieving more efficient access to the idle frequency band and spectrum sharing. It also limits and reduces the occurrence of collisions, so that the spectrum is more efficiently and rationally used.

In order to effectively implement the concept of cognitive radio networks, CR systems need to have the ability to perform the following functions [1]: spectrum sensing [2,3], spectrum decision, spectrum sharing and spectrum mobility. The proposition of spectrum prediction makes spectrum sensing, spectrum decision and spectrum mobility more efficient and intelligent, which are all based on spectrum prediction. Spectrum prediction in cognitive radio networks is a challenging problem that involves several sub topics such as channel status prediction, PU activity prediction, radio environment prediction and transmission rate prediction. Among them, the study of channel state prediction can play a critical role in spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility research.

Since 2006, when Professor Acharga putted forward the concept of spectrum prediction, the spectrum prediction method had been continuously innovating and improving. At present, there are mainly three types of prediction algorithms: prediction algorithms based on Markov model; prediction algorithms based on regression analysis; and prediction algorithms based on neural networks. The prediction method based on the regression model has poor application performance, which can't do anything for predictions in a slightly more complicated environment and multi-step prediction. The Markov model-based prediction method needs to know the prior knowledge of the probability distribution of channel occupancy for equation establishment and parameter acquisition. The neural network model-based prediction method is complex and requires a large amount of data for network training. But it has high applicability and portability, and doesn't need any prior knowledge. With the development of artificial intelligence technology, deep learning technology has achieved good results in various fields, and neural network technology has become more mature. This paper will study the spectrum prediction technology based on recurrent neural network (RNN).

2 Related Work

With the development of artificial intelligence technology, many scholars have studied channel state prediction based on neural networks [4–7].

In 2010, Tumuluru et al. [8] proposed that the service characteristics of most licensed user systems encountered in real life are not prior knowledge. They use a neural network model, MLP, to design a spectrum predictor that does not require prior knowledge of the service characteristics of the licensed user system.

In 2011, Liang et al. [9] proposed a practical spectrum behavior learning method based on MLP. Through supervised learning, the state of different channels in future time slots (idle or busy) can be predicted. In 2011, Zhao et al. [10] proposed a spectrum prediction model based on neural network, which can predict the spectrum occupancy state by simulation.

In 2013, Nakisa et al. [11] proposed a spectrum prediction for multiple secondary users using RNN and time delay neural network (TDNN), but it is only a method of averaging each secondary user after prediction, not Multi-user joint prediction.

The recurrent neural network has long and short time memory characteristics, aiming to solve the time series problem with correlation. The channel state prediction problem can also be regarded as a kind of time series problem. It seems reasonable and effective to apply the recurrent neural network technology to the channel state prediction problem. This paper will deeply study the channel state prediction problem based on RNN.

3 Spectrum Prediction Based on Sequence to Sequence Network

3.1 Model Establishment

Spectral prediction is such a technique that through analyzing historical spectrum measurement data to obtain spectrum usage laws and to predict future spectrum usage states. According to the spectrum prediction results, the cognitive device can implement intelligent spectrum sensing and dynamic spectrum access, reducing time expenses, and improving communication quality. This paper makes use of the advantages of deep learning for the learning ability of complex models, and adopts the time series model, RNN. By using known historical spectral states, a spectrum predictor is trained to learn the laws of the frequency equipment to predict future spectral states.

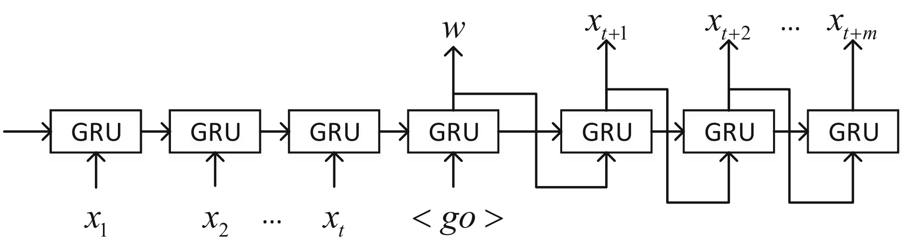

Fig. 1. Channel state prediction network structure based on seq-to-seq.

Figure 1 shows the structure of sequence to sequence neural network as used herein. When we predict the future channel states, we generally need to use the historical channel states, because in time, the channel states is not independent and has a certain time correlation. This is consistent with the structure of the RNN.

The left part of the model is the input module, and the channel states of n time slots are used as the input of the model. The right part is an output module that sequentially obtains channel state prediction values of m time slots by making use of a sequence of states of a certain length obtained from the input sequence. The predicted values are compared with the actual values, the error is propagated back, and the parameters of the model are updated.

The basic repeating module uses the GRU unit, which is a varient of RNN, and its basic structure is as shown in the Fig. 2.

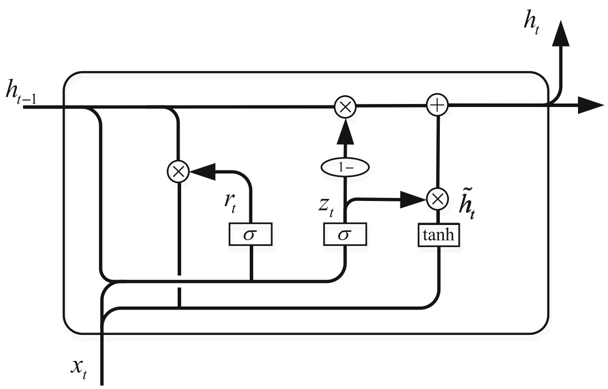

Fig. 2. GRU network structure.

The forward propagation update formula of the GRU unit satisfies:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{1}$$

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{2}$$

$$\widetilde{h}_t = tanh(W \cdot [r_t * h_{t-1}, x_t]) \tag{3}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \widetilde{h}_t \tag{4}$$

The output layer of the GRU uses the sigmoid activation function:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

Output layer:

$$a = y_t = \sigma(W_0 \cdot h_t + b) \tag{6}$$

Loss function:

$$C = -\frac{1}{n}\sum_x [ylna + (1 - y)ln(1 - a)] \tag{7}$$

Where n is the number of training data, y is the expected output, and a is the output of the neural network. the value of a is between (0, 1), indicating the probability that the channel state is busy. If it is greater than 0.5, the channel state is considered to be 1, and if it is less than 0.5, the channel state is considered to be 0.

In the training phase, we use the Adam optimizer, so that the cross entropy loss function is minimized, and the weight value is continuously adjusted according to the direction of the gradient decrease.

3.2 Performance Evaluation

Error Rate

$$P_p^e(Overall) \tag{8}$$

$P_p^e(Overall)$ is the percentage of the predictions that are incorrect in all predictions. It is the most important evaluation indicator reflecting the performance of the model.

Accuracy Rate

$$acc = 1 - P_p^e(Overall) \tag{9}$$

acc is equal to $1 - P_p^e(Overall)$, which is an evaluation method that positively reflects the performance of the model.

Probability of False Prediction in Case the Actual Channel Is Busy

$$P_p^e(Busy) \tag{10}$$

$P_p^e(Busy)$ is the percentage of the prediction result of 0 in the case where the real channel state is 1. It is a very important indicator, and often hope it can be as small as possible. Because when the channel state is occupied, if the prediction result is 0, the device will select the channel for sensing, which will waste a lot of sensing time. Therefore, this indicator is a very important evaluation indicator that the application users are more concerned about. From the perspective of the primary user, this indicator indicates the interference degree to the primary users.

Probability of False Prediction in Case the Actual Channel Is Idle

$$P_p^e(Idle) \tag{11}$$

$P_p^e(Idle)$ is the percentage of the predict result of 1 in the case where the real channel state is 0. It is an indicator that affects the $P_p^e(Overall)$.

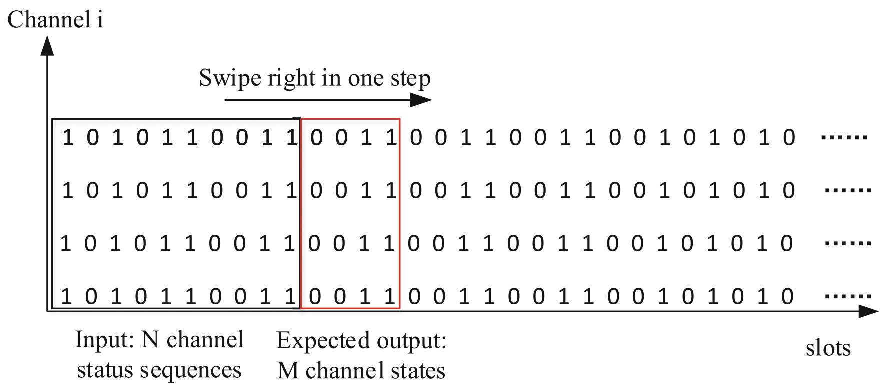

Fig. 3. Data processing process

3.3 Data Sampling Process

The channel state data is sliced, and each slice is composed of channel states of a certain length of time. Each channel state sequence is input into the model to obtain a corresponding output (i.e., the prediction results of the future channel states). The data processing process is shown in Fig. 3.

3.4 Parameter Settings

In the channel state prediction model of the GRU-based seq-to-seq network, the number of neurons of the GRU basic unit is 20, the learning rate is set to 0.01, and the batch size is set to 100. Compared with the MLP model, the structure of the two hidden layers is used. The number of neurons in the first layer is 8, the number of neurons in the second layer is 4, the learning rate is set to 0.001, and the number of trainings is set to 1000. The weights, initial state values, and deviations used therein are randomly generated using a random function.

4 Simulation Results and Analysis

4.1 The Effect of Input Sequence Length on the Model Performance

There are many factors affecting performance. When the input sequence length of the model is different, the performance of the model is different. Therefore, we have carried out experiments on the length of the input sequence from 1 to 20. The experimental data in this paper is generated using the $M/M/1$ queuing system model. Two fixed modes have been added. Figure 4 shows the trends of the $P_p^e(Overall)$, $P_p^e(Busy)$, $P_p^e(Idle)$ for different input sequence lengths.

It can be seen from Fig. 4 that when the input sequence length becomes larger, the $P_p^e(Overall)$, $P_p^e(Busy)$, $P_p^e(Idle)$ of the model tends to decrease. Extremely, when the input sequence length is 1 time slot, the performance of

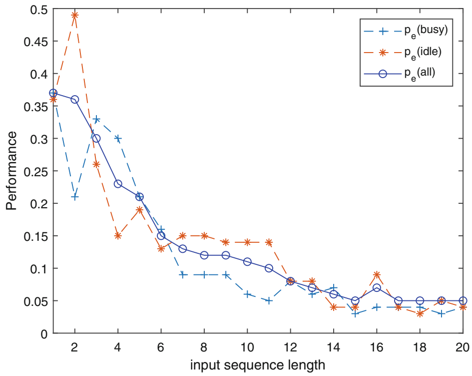

Fig. 4. Performance varies with input sequence length.

the model is the worst. The basic principle is the same as the statistical method. The historical information used has only 1 time slot, and the prediction accuracy is very low. The more the length of the input sequence, the more the historical information can be obtained and the higher the prediction performance will be. When the length is increased to a certain length, the performance is almost stable because the data used by the model itself has a finite length of dependence on historical data. Therefore, when the input sequence length of the model grows beyond the duration of the dependency in the data, it will not have more impact on performance, which just takes advantage of the time-dependent nature of the GRU.

In the case where the input sequence length is 20, the predicted result is obtained by using the trained model. The result of intercepting 100 time slots is shown in Fig. 5. Where blue represents the true value and red represents the prediction result. It can be seen that most of the predicted values are consistent with the true values, and only a small part are inconsistent with the real results.

4.2 Comparative Analysis of Performance Between MLP Network and the Proposed Method

In this paper, the MLP network is used for comparison experiments with the seq-to-seq network. The MLP network parameters are set as described above.

The performance of the MLP varies with the length of the input sequence, as is shown in Fig. 6. As can be seen from the figure, the performance of the MLP eventually converges to an error rate of 0.1, which is much worse than the seq-to-seq network converging to an error rate of 0.03.

In addition, a performance comparison chart between the MLP network and the method of this paper is given, as is shown in Fig. 7, taking the acc as an example. As can be seen from Fig. 7, the proposed method is much better than the MLP network. Extremely, when the input sequence length is 1, there is no difference between the two methods. When the input sequence length is small,

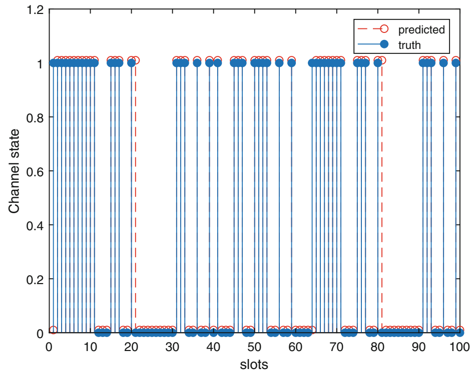

Fig. 5. Comparison of predicted results with real values. (Color figure online)

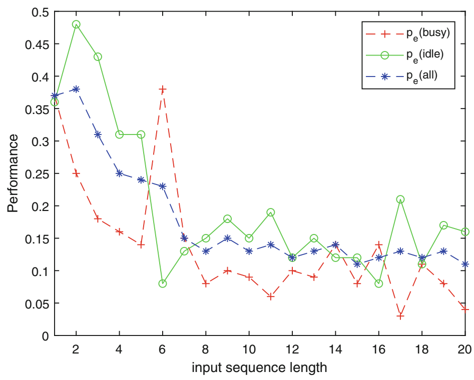

Fig. 6. MLP performance varies with input sequence length

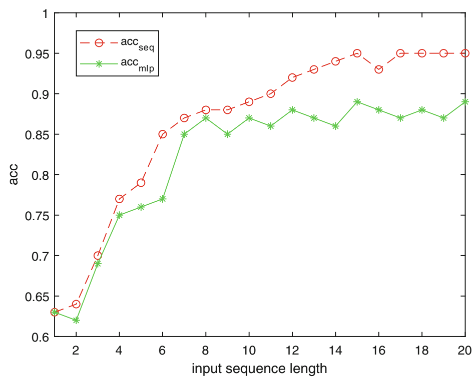

Fig. 7. MLP and seq-to-seq performance comparison chart

there is little difference. When the input sequence length is greater than 8, the prediction accuracy of this paper is much higher than the prediction accuracy of the MLP network, and the best case is 10% higher.

4.3 The Effect of Output Sequence Length on the Model Performance

When the channel occupancy is equal to 0.5 and the input slot length is fixed to 15 slots, the effect of the output sequence length on the model performance will be discussed below. In this paper, the output sequence length is changed from 1 to 15. Experiments are performed to record the $P_p^e(Overall)$, $P_p^e(Busy)$, $P_p^e(Idle)$ of the seq-to-seq model, as is shown in Fig. 8.

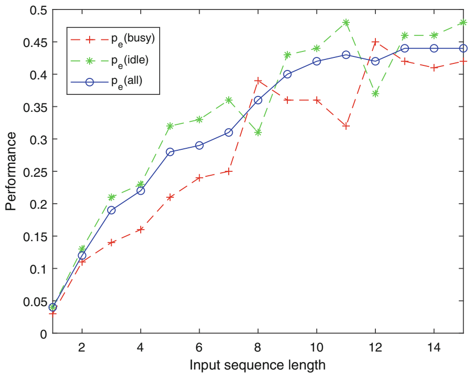

Fig. 8. Performance vs. predicted time slot length.

As can be seen from Fig. 8, when the output sequence length changes from 1 to 15, the error rate of the model changes from 0.03 to 0.44. This shows that the more time slots are predicted, the smaller the accuracy will be. This is also consistent with the actual situation.

In particular, in the case of predicting multiple slots, a slot-by-slot analysis is performed to understand the prediction performance variation of a single slot in the case of multi-slot prediction. In the case where 15 slots are selected for prediction, the performance variation of the i-th slot is considered. The correct rate of the i-th time slot is shown in Fig. 9.

As can be seen from Fig. 9, when predicting the length of 15 time slots. The farther the time slot is, the lower the correct rate will be, ie, the lower the certainty and the more unpredictability.

4.4 Joint Prediction of Multiple Channels

In this section, the joint multi-slot prediction of four channels is to treat the four channels as a whole one, which are related to each other, instead of four

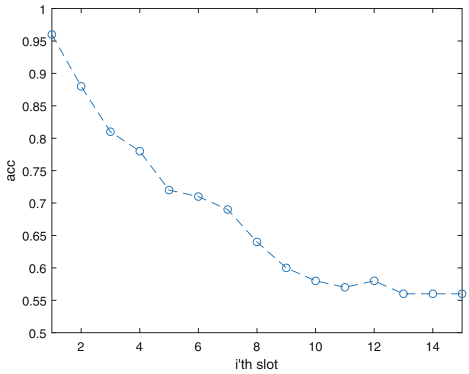

Fig. 9. In the case where the output sequence length is 15, the correct rate of the i-th time slot.

channels independent of each other. This paper compares the four channel joint prediction with the independent prediction. When the predicted time slot length is 1, and the input time slot length is changed from 1 to 15, the performance change of the $P_p^e(Overall)$, $P_p^e(Busy)$, $P_p^e(Idle)$ are shown in Fig. 10.

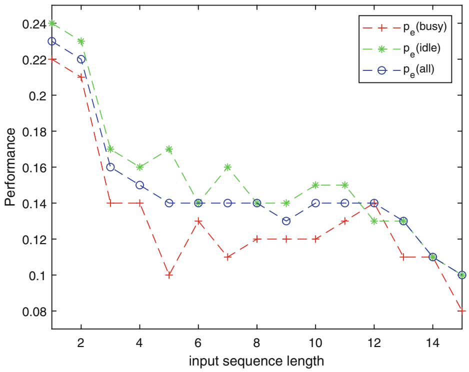

Fig. 10. Influence of input sequence length on multi-channel prediction performance

As can be seen from Fig. 10, as with single-slot prediction, the more the input sequence length, the lower the error rate. When the input sequence length is changed from 1 to 15, the error rate is changed from 0.23 to 0.1.

As a comparative experiment, the four channels are regarded as independent and uncorrelated, and they are independently predicted by single channel prediction. The total prediction accuracy of the four channels is compared to the joint prediction results. As is shown in Fig. 11.

Figure 11 is a comparison of the total correct rate in the four channels of joint prediction and separate independent prediction. As can be seen from Fig. 11, the

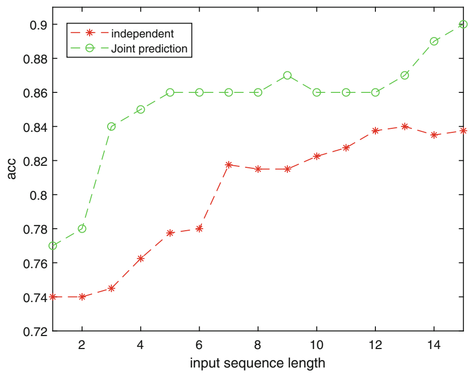

Fig. 11. Comparison of correct rate between multi-channel joint prediction and independent prediction

correct rate of joint prediction is 3%–6% higher than the accuracy of independent prediction. This is because when joint prediction, both the channel state of the historical time slot of the channel and the state of the historical time slot of other channels can be considered, and the mutual influence between the channels has an influence on the result of the channel.

5 Summary

In this paper, the correlation characteristics of the channel state in time are fully considered, and the seq-to-seq network structure based on the recurrent neural network is applied to the spectrum prediction problem, which has the characteristics of long and short time memory function. It is studied how to use the channel state values of n historical time slots to predict the channel state values of the future m time slots. We discussed the effect of the input sequence length n on the prediction accuracy. The effect of the output sequence m on the performance is also discussed. Moreover, with the seq-to-seq network structure, simultaneous joint prediction for multiple channels is also possible. And this paper also discussed the performance difference between multi-user joint prediction and single user independent prediction.

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