A Spectrum Prediction Technique Based on Convolutional Neural Networks

Jintian Sun(✉), Xiaofeng Liu, Guanghui Ren, Min Jia, and Qing Guo

School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin 150001, China
18s105097@stu.hit.edu.cn, jiamin@hit.edu.cn

Abstract. Secondary users in cognitive radio system use spectrum sensing technology to detect the primary users in the frequency band and use spectrum holes to communicate. Spectrum prediction technology is based on the existing spectrum sensing results to predict the future channel occupancy, so as to reduce the blocking rate, avoid malicious dynamic interference and other purposes. In this paper, a spectrum prediction method based on convolution neural network is proposed and some applications of this method in practical communication systems are given. This method can be trained in real time and has a certain adaptability to the dynamic environment. Using this method, the predicted results can be used to allocate resources reasonably, and the spectrum resource utilization rate is high. In addition, the time-consuming of broadband spectrum sensing can be shortened by combining the spectrum prediction method based on convolution neural network. At the end of this paper, the simulation results of spectrum prediction method based on convolution neural network are given and the efficiency of the algorithm is discussed.

Keywords: Cognitive radio · Spectrum prediction · Convolution neural network

1 Introduction

In recent years, the number of mobile wireless communication devices continues to grow, and the types of services are complex and diversified, which has led to a surge in demand for spectrum resources. On the other hand, there is a lot of waste in the existing spectrum resource allocation schemes. Cognitive radio (CR) is an important technology to solve the contradiction between the shortage of spectrum resources and the low utilization of spectrum resources. Using this technology, unauthorized secondary user (SU) can sense the spectrum environment and access the idle frequency band that the authorized primary user (PU) does not use temporarily, effectively improve the utilization of spectrum resources, to a certain extent, solve the problem of spectrum resource shortage.

However, in current CR technology, it is common for SU to sense the idle channel in the frequency band and occupy it for data transmission, and continuously sense the current channel while communicating, stop the transmission immediately when the PU reactivate signal is received, and then re-select other idle channels. However, when the

M. Jia et al. (Eds.): WiSATS 2019, LNICST 280, pp. 69–77, 2019.
https://doi.org/10.1007/978-3-030-19153-5_7

number of PUs is large and they frequently access/leave the channel or have dynamic malicious interference in the available frequency band, SU needs to frequently re-sensing the spectrum environment, re-select the channel and retransmit the data. This will result in the waste of SU resources, the increase of communication delay, the increase of packet loss rate and the decrease of throughput. Moreover, this problem is particularly serious when the frequency band of the system is wide and the spectrum sensing time is long.

Spectrum prediction technology is an effective way to solve the above problems. Its basic principle is to predict whether the channel will remain idle in the future by some method, so as to select a good channel to access. At present, there are some related researches, such as spectrum prediction based on hidden Markov model [1–3] de, spectrum prediction based on BP neural network [4] and many improved methods based on it [5, 6], spectrum prediction based on Q-learning [7], etc. The spectrum prediction based on Markov model needs to know some prior information about the spectrum environment in advance, which is often difficult to obtain. BP neural network needs to train a fully connected neural network. Generally, the weight of this network is very large and needs a large number of training samples. In addition, most of the above spectrum prediction methods are not easy to change after the model is determined, cannot adapt to the dynamic environment, and can only output an optimal channel. Q-learning and spectrum waterfall model are used to deal with dynamic interference [8], but the relationship between the algorithm and spectrum prediction is not discussed.

To solve above problems, this paper presents a spectrum prediction technique based on convolution neural network (CNN) classification model, and gives its application in practical communication system. The main features are as follows:

1. After completing the model training, we can continue to train in real time and have better dynamic environment adaptability.
2. It can output more than one good channel with long idle time in the future, so as to allocate resources reasonably to SU in the future.
3. By sharing spectrum prediction and spectrum sensing information, spectrum sensing aided spectrum prediction is realized, and spectrum prediction guides spectrum sensing, thus saving overall time consumption.
4. Using relay cooperative spectrum sensing and data fusion center, SU resources are allocated reasonably to improve resource utilization efficiency.

2 System Model and Problem Description

It is assumed that there are multiple PU using frequency bands $F = [f_1, f_2]$ to communicate in one area. At the same time, some SU want to use the same frequency band F for communication. These SUs do not have spectrum sensing capabilities, and all spectrum sensing tasks are handed over to a cognitive data fusion center (DFC) in the region [9]. DFC continuously senses frequency band F by periodic T, and divides F into N channels according to the communication bandwidth requirement of SU, which are $c_1, c_2, \cdots c_N$. At time t, the DFC senses the spectrum of the current environment, and then decides whether there is a PU in the channel $c_n (n = 1, 2, \cdots, N)$ according to energy detection [10]. The binary detection model for the detection of PUs in the AWGN channel can be written as:

$$\begin{cases} c_n = 0 & : \quad r(t) = n(t) \\ c_n = 1 & : \quad r(t) = x(t) + n(t) \end{cases} \tag{1}$$

Where $x(t)$ is the PU signal in the current detection channel, and $n(t)$ is the Gaussian white noise with the double-band power spectral density N_0. Take the test statistic as:

$$V(t) = \frac{1}{N_0} \int_{t-T}^{t} r^2(t) dt \tag{2}$$

After setting the threshold with a certain false alarm probability, it is possible to detect whether there is a PU in the c_n with a certain detection probability. If there is no PU in c_n at t time, that is, channel c_n can be called as $c_n = 0$, otherwise it is called $c_n = 1$. And all channel occupancy conditions at time t are defined as the channel environment state vector s_t at time t. The element in this $1 \times N$ vector is only 0 or 1. All the environment state vectors from time $t - (m-1)T$ to time t are defined as the channel environment state matrix $S_t = \{s_{t,1}, s_{t,2}, \cdots s_{t,N}\}$ in chronological order. Obviously, S_t is a matrix of $m \times N$, of which elements are only 0 or 1. In addition, $C_{t,1}$, is defined as the longest idle channel number after t. Define $C_{t,2}$, whose value is equal to the channel number of second long idle time after t time. And so on.

If the current time is recorded as t_c. Our problem is how to predict $C_{t_c,1}, C_{t_c,2}, C_{t_c,3} \cdots$ in the case of known $S_{t_c}, S_{t_c-T}, S_{t_c-2T} \cdots$. These predicted results are used to allocate resources reasonably, so as to reduce the collision between SU and PU as much as possible, avoid waste of resources, and ultimately improve the overall performance of the system. Using CNN based spectrum prediction technology can accomplish this task.

3 CNN-Based Spectrum Prediction Technology

Enlightened by the good performance of CNN in image classification and recognition, this idea can be applied to spectrum prediction. When using CNN to classify and recognize images, a certain number of pictures and labels which can correspondingly represent the content of each picture are needed to make a data set, and then the data set is used to train a well-designed CNN structure. After getting a trained CNN, the new picture can be input into the CNN to determine the category of the picture with high accuracy [11]. Based on the similarity between picture and channel environment state matrix, label and channel number, a spectrum prediction technique based on CNN is proposed.

As shown in Fig. 1, for simplicity, the principle of spectrum prediction based on CNN is illustrated by predicting the optimal channel $C_{t_c,1}$ at the current time, (similarly $C_{t_c,2}, C_{t_c,3} \cdots$).

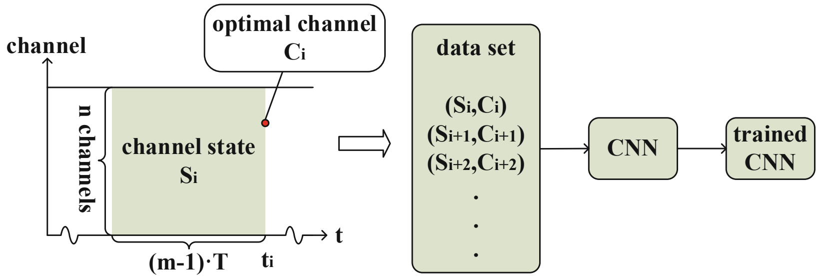

Fig. 1. Schematic diagram of spectrum prediction technology based on CNN.

The first is the training session. At the time t_i, DFC can obtain channel environment state matrix S_{t_i} and optimal channel $C_{t_i,1}$, abbreviated as S_i and C_i by spectrum sensing. The channel environment state matrix S_{t_i+T} and the optimal channel $C_{t_i+T,1}$, which are abbreviated as S_{i+1} and C_{i+1} respectively, can be obtained from the DFC at the time of $t_i + T$ by spectrum sensing. Many pairs of spectrum state, optimal channel pairs $(S_i, C_i), (S_{i+1}, C_{i+1}), (S_{i+2}, C_{i+2}), \cdots$ can be obtained by many times of spectrum sensing. Use them as data and labels to input CNN as a training set and train CNN accordingly.

Then the prediction session. At time t_n, the channel environment state matrix S_{t_n} can be obtained by DFC through spectrum sensing, and the optimal channel $C_{t_n,1}$ can be obtained by inputting S_{t_n} into the trained CNN.

The CNN-based spectrum prediction technique has the following two features worthy of explanation.

Training a CNN requires data and data corresponding labels. Generally speaking, when a trained CNN is in use, only data is input into the network, and it is impossible to determine whether the network output is correct or not. This has led to the inability to adjust network parameters after the training is over. For the spectrum prediction technology based on CNN, the label is the future idle channel number. Therefore, in actual applications, not only data can be obtained, but also a label corresponding to the data can be obtained after a short delay. That is to say, new training data sets can be obtained during use. These new data sets can be used to fine-tune existing network parameters in real time if necessary. Thereby further improving the prediction accuracy and enabling the system to obtain a certain dynamic environment adaptability.

Generally speaking, a CNN contains many parameters, and forward propagation takes a long time. However, spectrum prediction technology based on CNN can solve this problem by using the characteristics of channel environment state matrix. The value and arrangement of most data in the channel environment state matrix at the adjacent time are exactly the same. For example, at time t, $S_t = \{s_{t,1}, s_{t,2}, \cdots s_{t,N}\}$, at the adjacent time $t + T$, $S_{t+T} = \{s_{t+T,1}, s_{t+T,2}, \cdots s_{t+T,N}\}$, there is

$$s_{t,k} = s_{t+T,k-1}, (k = 2, 3, \cdots, N) \tag{3}$$

$$S_{t+T} = \left\{ s_{t+T,1}, s_{t+T,2}, \cdots, s_{t+T,N-1}, s_{t+T,N} \right\} = \left\{ s_{t,2}, s_{t,2}, \cdots, s_{t,N}, s_{t+T,N} \right\} \quad (4)$$

S_{t+T} can be viewed as a result of translation and additions and deletions of S_t. Because of the principle of data forward propagation in CNN [11], when the adjacent data is highly repeatable, most of the data in the convolution layer and pool layer of CNN need not be recalculated in the two forward propagation calculations at adjacent times. Although the fully connected layer does not have this property, in most cases the computational complexity of the fully connected layer is much less than that of other hidden layers. In practical application, the corresponding intermediate results of the previous time operation can be saved, and then the changed data are calculated and combined with the saved data in the next calculation. This can greatly reduce the time of forward propagation.

Based on the same principle, training multiple different CNN can predict $C_{t_c,2}, C_{t_c,3} \cdots$ respectively. When several SUs have service requirements, DFC can reasonably allocate channel resources according to the demand of SU for channel idle time. Avoid waste of resources and improve resource utilization.

In addition, when there is malicious dynamic interference in the environment, the interference signal will be directly regarded by the SU as a PU. Therefore, based on the same principle, this method can also be applied to avoid malicious dynamic interference.

4 Combination of Spectrum Prediction and Spectrum Sensing

In addition to the channel selection for SU based on the spectrum prediction results mentioned above, spectrum prediction can also be used to speed up spectrum sensing.

When the available frequency band is wider, the longer spectrum sensing time will reduce the overall performance of the system. The traditional idea is to use compressed sensing algorithm or other solutions to solve this problem [12]. The application of spectrum prediction technology can solve this problem from another angle.

As shown in Fig. 2, suppose the system works in a relatively wide bandwidth environment. Firstly, data fusion center A performs full-band spectrum sensing for a period of time, and trains CNN with the sensing results. The trained CNN is used to predict several channels $\{C_1, C_2, C_3 \cdots\}$, which will remain idle for some time in the future, through the current channel environment state matrix S. At this point, the full-band spectrum sensing is no longer carried out, but narrow-band spectrum sensing is carried out for several bands where $\{C_1, C_2, C_3 \cdots\}$ are located. After a period of time, the full band spectrum sensing is resumed to cope with environmental changes. After that, repeat the above process. In summary, spectrum sensing results are used to complete the spectrum prediction, and then the spectrum prediction results are used to guide the next period of spectrum sensing. With this method, SU can be accessed more quickly when the service requirement of SU occurs in the partial spectrum sensing stage. This method reduces the overall system delay from reducing the average time of spectrum sensing.

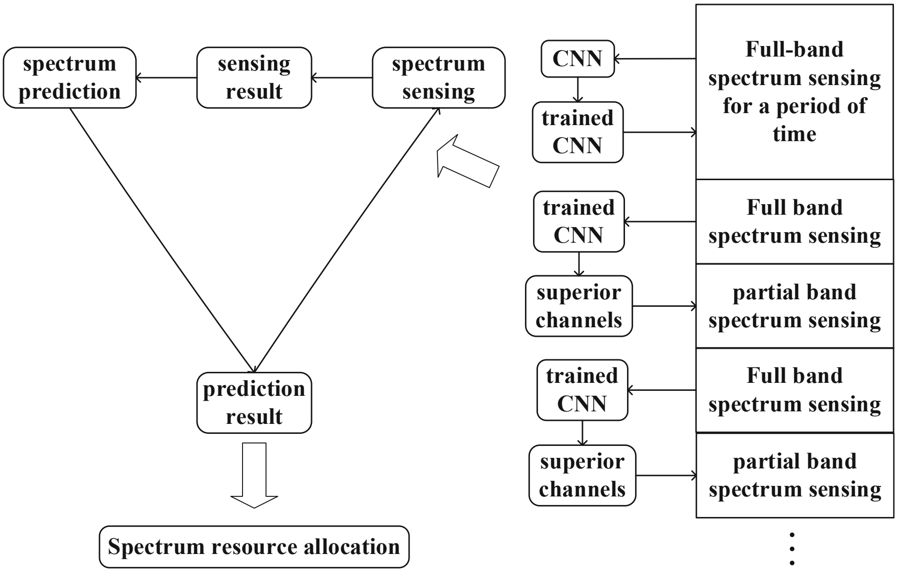

Fig. 2. The process of combining spectrum sensing with spectrum prediction.

5 Numerical Results and Discussion

In this paper, a simple CNN is designed, which contains two convolution layers and a full connection layer. The activation functions use tanh function, and the output data of convolution layer is pooled by 2×2 average. The output layer function uses the softmax function.

First, the idle channel prediction capability of CNN-based spectrum prediction technology is simulated. The simulation parameters are set such that the PU number obeys the Poisson distribution with the parameter λ at each perception. The size of the channel state matrix S_t is set to 200×9. In order to assess the performance of the proposed algorithm, the blocking rate of the proposed spectrum prediction algorithm is compared with the blocking rate based on BP neural network spectrum prediction. The parameter for assessment is the reduction rate of blocking rate relative to accessing by a random selection of all idle channels.

$$\Delta R = \frac{r_0 - r}{r_0} \tag{5}$$

Where ΔR means the reduction rate of blocking rate, r means the blocking rate of using spectrum prediction algorithms, r_0 means the blocking rate of accessing by a random selection of idle channels. Obviously, higher ΔR means better performance of the algorithm. The ΔR of various spectrum prediction algorithms change with training times under different λ settings are shown in Fig. 3. In Fig. 3, the red solid line represents using CNN-based spectrum prediction, the black dotted line represents using

BP neural network spectrum prediction, and the blue dotted line represents a random selection of idle channels.

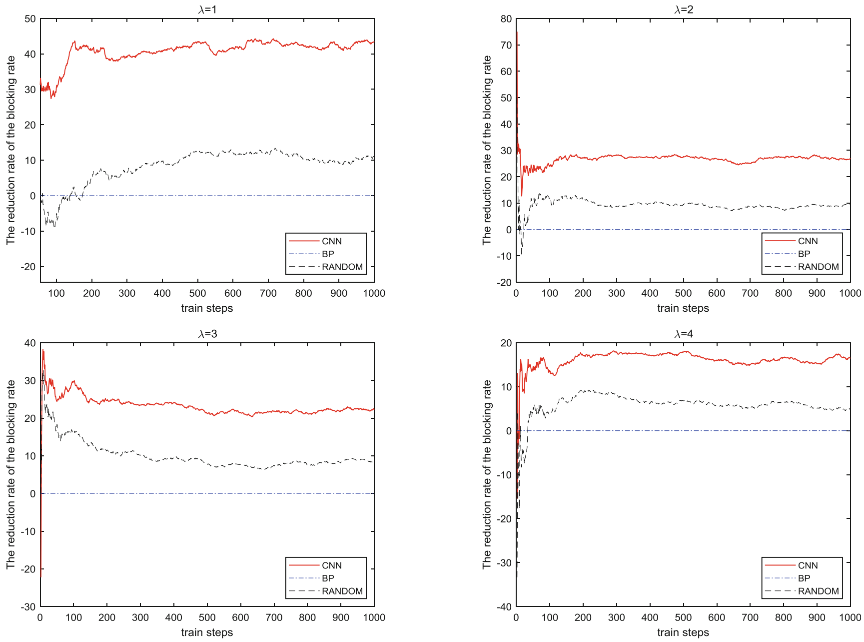

Fig. 3. Relationship among ΔR, train steps, idle channel selection strategies and λ (Color figure online)

After the training results have stabilized. It can be seen that when $\lambda = 1, 2, 3, 4$ the ΔR of CNN-based spectrum prediction is approximately equal to 40%, 25%, 20% and 15%. But the ΔR of BP neural network spectrum prediction is always lower than 10%. The performance of CNN-based spectrum prediction is always better than BP neural network spectrum prediction under various user densities.

After that, the CNN-based spectrum prediction technology was simulated to avoid malicious interference. The interference type is set to sweep interference with an unknown frequency hopping interval. The interference power is set to be much higher than the user's signal power. The user can hop frequency once every 10 spectrum sensing periods at the fastest.

In Fig. 4, the yellow strip indicates the channel on which the frequency sweep interferes at each moment. The green block is the channel that the user selects through spectrum prediction. It can be seen that the user avoids malicious interference under the support of spectrum prediction technology. From the results, when the interference mode is relatively fixed, it only takes dozens of rounds of training to complete the task of avoiding interference.

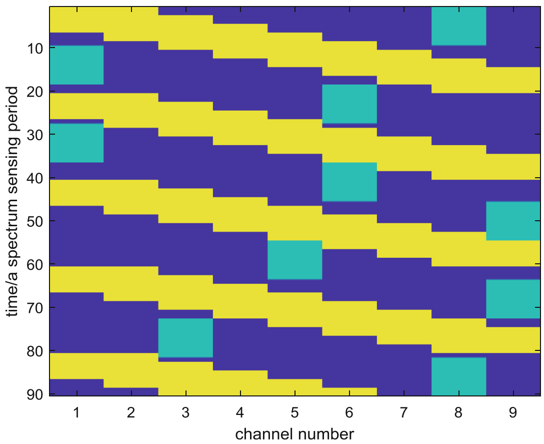

Fig. 4. Users avoid malicious interference through spectrum prediction (Color figure online)

6 Conclusion and Outlook

This paper proposes a new spectrum prediction technology for the problems faced by SU in the existing CR. This technique is applied to reduce blocking rate, avoid malicious dynamic interference, spectrum resource allocation and wideband spectrum sensing. And have a good application effect. However, the method has high requirements on the computing power of the device, and the energy consumption in the actual application is also high. This is a common problem of artificial neural networks. The focus of future research should be on how to reduce the amount of system computation as much as possible while continuing to maintain a high probability of accurate prediction. Thereby reducing system hardware requirements.

Acknowledgement. This work was supported by the National Natural Science Foundation of China (No. 61671183, 61771163 and 91438205) and the State Key Laboratory of Space-Ground Integrated Information Technology (2015_SGIIT_KFJJ_TX_02).

References

1. Eltom, H., Kandeepan, S., Liang, Y.C., Evans, R.J.: Cooperative soft fusion for HMM based spectrum occupancy prediction. IEEE Commun. Lett. **22**(10), 2144–2147 (2018)
2. Saad, A., Staehle, B., Knorr, R.: Spectrum prediction using hidden Markov models for industrial cognitive radio. In: IEEE International Conference on Wireless and Mobile Computing (2016)
3. Eltom, H., Kandeepan, S., Liang, Y.C., Moran, B., Evans, R.J.: HMM based cooperative spectrum occupancy prediction using hard fusion. In: IEEE International Conference on Communications Workshops (2016)
4. Bai, S., Zhou, X., Xu, F.: "Soft decision" spectrum prediction based on back-propagation neural networks. In: International Conference on Computing. IEEE (2014)

5. Supraja, P., Pitchai, R.: Spectrum prediction in cognitive radio with hybrid optimized neural network. Mob. Netw. Appl. 1–8 (2017)
6. Bai, S., Zhou, X., Xu, F.: Spectrum prediction based on improved-back-propagation neural networks. In: International Conference on Natural Computation. IEEE (2016)
7. Han, G., Xiao, L., Poor, H.V.: Two-dimensional anti-jamming communication based on deep reinforcement learning. In: Proceedings of the 42nd IEEE International Conference on Acoustics, Speech and Signal Processing, March 2017
8. Liu, X., Xu, Y., Jia, L., Wu, Q., Anpalagan, A.: Anti-jamming communications using spectrum waterfall: a deep reinforcement learning approach. IEEE Commun. Lett. **22**(5), 998–1001 (2017)
9. Wu, K., Tang, M., Tellambura, C., Ma, D.: Cooperative spectrum sensing as image segmentation: a new data fusion scheme. IEEE Commun. Mag. **56**, 143 (2018)
10. Ali, A., Hamouda, W.: Advances on spectrum sensing for cognitive radio networks: Theory and applications. IEEE Commun. Surv. Tutor. **19**(2), 1277–1304 (2017)
11. Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, pp. 1097–1105 (2012)
12. Qin, Z., Gao, Y., Plumbley, M.D., Parini, C.G.: Wideband spectrum sensing on real-time signals at sub-Nyquist sampling rates in single and cooperative multiple nodes. IEEE Trans. Signal Process. **64**(12), 3106–3117 (2016)