A Brief Review of Machine Learning Algorithms for Cooperative Spectrum Sensing

Jingting Wang¹ and Bao Liu²,*

¹Department of Engineering and Technology, Xi’an Fanyi University, Xi’an, China
²College of Electrical and Control Engineering, Xi’an University of Science and Technology, Xi’an, China

*Corresponding author e-mail: baoliu@xust.edu.cn

Abstract. With the development of wireless communication services, spectrum resources become more and more scarce. Cognitive radio technology is widely considered as a feasible solution to the problem of spectrum sharing. The introduction of machine learning has greatly promoted the cooperative spectrum sensing of cognitive radio. In particular, this paper briefly reviews the cooperative schemes in three machine learning algorithms, including support vector machine, Convolutional Neural Network, and deep reinforcement learning. It is worth summarizing and discussing these machine learning cooperative spectrum sensing algorithms.

Keywords: Cooperative Spectrum Sensing, Cognitive Radio, Machine Learning

1. Introduction

The limited resource of wireless spectrum is the basis of wireless communication [1]. However, spectrum resources have become a scarce resource because of the expansion of service demand. Among many solutions, cognitive radio is considered to be one of the most potential spectrum sharing technologies, whose core idea is to use the spectrum resources when the spectrum channel is idle by using the dynamic spectrum access technology, so as to improve the spectrum utilization. In this process, the following five key technologies are involved, including spectrum sensing, analysis, decision-making, sharing, and handoff [2]. As the basis of cognitive radio, spectrum sensing determines the future of spectrum sharing technology.

Cognitive users need to distinguish the useful signal or noise in the monitoring frequency band through spectrum sensing technology, so as to determine whether the frequency band is busy with the primary user [3, 4]. If the frequency band is idle, then the frequency band be used by cognitive users. As the basis of spectrum discovery, spectrum sensing makes spectrum sharing possible, which is the primary task of cognitive radio technology.

Due to the limitation of the hardware sensing system, the detection ability of narrowband signal is limited in the initial stage. Spectrum sensing algorithms include two categories according to the number of cognitive users, e.g. single user (node) spectrum sensing algorithm and cooperative spectrum sensing (CSS) algorithm [5]. Because a single user (node) does not have the ability to receive multiple antennas, its spectrum sensing algorithm is difficult to resist the adverse factors such
as deep fading and shadow shading. Therefore, the existing spectrum sensing algorithms mainly focus on the cooperative one, which ensures the detection efficiency and reduces the detection time. The basic operating mechanism of cooperative spectrum sensing is shown in Figure 1. In cooperative sensing, each secondary user participates in spectrum sensing as a local sensing terminal, and the local sensing results of secondary users will converge to a fusion center (FC) through the common control channel. The data fusion center will fuse the collected local sensing results according to a fusion rule, and make a final judgment of the current channel state according to the fusion results.

![Figure 1. The basic operating mechanism of cooperative spectrum sensing](image)

Recently, some machine learning algorithms were introduced in CSS [6, 7], and a very good spectrum sensing effect is achieved in terms of detection accuracy and detection time. In this paper, we survey the machine learning algorithms to improve the classification performance of cooperative spectrum sensing.

2. Problem Formulation

A cognitive radio network is shown in Figure 1 which consists of one fusion center (FC), $M$ secondary users (SUs), and one primary user (PU). It is assumed that each secondary user acquires energy perception independently. $y_{k,m}$ is a PU local energy perceived by the $m$th SU at sensing time $k$, and the energy vector $y_k = (y_{k,1}, y_{k,2}, \ldots, y_{k,m}, \ldots, y_{k,M})$ at the FC side [8].

Usually, the CSS problem would be formulated to a binary hypothesis testing problem with two hypotheses, $H_0$ vs. $H_1$, for the SUs: i.e., whether the frequency is busy ($H_1$) or idle ($H_0$) [9]. Specifically, the CSS energy detection hypothesis testing problem can be described as follows [10, 11]

$$x_m(t) = \begin{cases} v_m(t) & H_0 \\ v_m(t) + h_m \cdot s(t) & H_1 \end{cases}$$

(1)

where $v_m(t)$ represents the noise signal received by the $m$th SU, $t = 1, 2, \ldots, N$, and $m = 1, 2, \ldots, M$; $s(t)$ is the PU signal at time $t$, and $h_m$ represents the frequency channel gain, which is assumed to be constant during the spectrum vacancy detection period [12]. The energy estimator $y_{k,m} = \sum_{r=1}^{N} |x_m(t+kN)|^2$, where $k = 1, 2, \ldots, K$ is the time index.
3. Structure of Machine Learning CSS

Cooperative spectrum sensing is described as a binary hypothesis testing problem, or a classification problem. Therefore, the idea of introducing machine learning algorithm into cooperative spectrum sensing is quite natural. The data set is divided into two parts, and one is the training set, and the other is the test set. The machine learning algorithm is used to construct the classifier, and the optimal parameters of the classifier are obtained through the training data set. Then, the test set is used to test the optimal parameters of the classifier to ensure the classification accuracy of cooperative spectrum sensing.

Collecting energy vectors \( y_k = \left( y_{k,1}, y_{k,2}, \ldots, y_{k,m}, \ldots, y_{k,M} \right) \) as the data sets is the first priority. In order to make full use of the detection effectiveness of supervised learning, the training data set should include the label which indicates the frequency is busy or idle. The machine learning based CSS framework is shown in Figure 2. After the machine-learning algorithm, the classifier will provide the sensing result that the PU is present or not [8].

![Figure 2. The machine learning CSS framework](image)

4. Review of Machine Learning based CSS

4.1. Support Vector Machine for CSS [8]

The purpose of support vector machine (SVM) algorithm is to find the classification hyperplane which maximizes the classification interval while meeting the requirements of classification accuracy. It is required to maximize the classifier margin and minimize the sum of errors,

\[
\min_{\omega} \frac{1}{2} \|\omega\|^2 + D \sum_{k=1}^{K} \xi_k
\]

s.t. \( \Gamma_k \left[ \omega \cdot \phi(y_k) + c \right] \geq 1 - \xi_k, \xi_k \geq 0, k = 1, 2, \ldots, K \)

where \( \|\omega\|^2 = \omega \cdot \omega \), and \( D \) is a soft margin constant, and \( c \) is a bias, and \( \xi_k \) is a relaxation factor, and \( \phi \) is a non-linear mapping function, and \( \Gamma_k = 1 \) or \(-1\).

The Lagrangian function of equation (2) can be expressed as
\[ L(\omega, c, \xi, \lambda, \gamma) = \frac{1}{2} \| \phi \| + D \sum_{k=1}^{K} \xi_k - \sum_{k=1}^{K} \lambda_k \left( \Gamma_k \left[ \omega \cdot \phi(y_k) + c \right] - 1 + \xi_k \right) - \sum_{k=1}^{K} \gamma_k \xi_k \]  \tag{3}

where \( \lambda_k \) and \( \gamma_k \) are Lagrangian multipliers. The equation (3) can be rewritten as a corresponding dual problem

\[
\max_j \sum_{k=1}^{K} \lambda_k - \frac{1}{2} \sum_{i=1}^{K} \sum_{j=1}^{K} \lambda_i \lambda_j \Gamma_i \Gamma_j \left( \phi(y_i), \phi(y_j) \right) \quad \text{s.t.} \sum_{k=1}^{K} \lambda_k \Gamma_k = 0, 0 \leq \lambda_k \leq C
\]  \tag{4}

Assume the solution is \( \lambda_i^* \), then \( \omega^* = \sum_{k=1}^{K} \lambda_k \Gamma_k \phi(y_k) \). The optimal bias is \( c^* = \Gamma_k - \sum_{i=1}^{K} \Gamma_i \lambda_i \phi(y_i) \cdot \phi(y_k) \) and the optimal classifier is \( f(y) = \text{sgn} \left( \sum_{k=1}^{K} \lambda_k \Gamma_k \kappa(y, y_k) + c^* \right) \), where \( \kappa(y, y_k) = \phi(y) \cdot \phi(y_k) \) is the kernel function.

4.2. Convolutional Neural Network for CSS [13]

Convolutional neural network (CNN) is introduced into the cooperative spectrum sensing algorithm, and the energy vector is used to calculate the action-value function [14, 15] in order to classify the busy or idle of the frequency. The CNN consists of three different sub-blocks, e.g. convolutional layer, rectifier linear unit (ReLU), and max-pooling layer. The input energy vectors \( y_k = (y_{k,1}, y_{k,2}, \ldots, y_{k,m}, \ldots, y_{k,M}) \) are entered into the convolution part of CNN, Second, the rectifier linear unit chooses the maximum value among the input and zero. Third, the max-pooling unit chooses the maximum entry of the energy vector.

4.3. Deep Reinforcement Learning for CSS [15]

In the deep reinforcement learning cooperative spectrum sensing algorithm, the input is the number of secondary users and energy vectors \( y_k = (y_{k,1}, y_{k,2}, \ldots, y_{k,m}, \ldots, y_{k,M}) \), and the output is the classification result of whether the primary user exists or not. The sensing energy of each secondary user is collected to form the energy vector data set, and the classification result of global sensing is obtained through calculation. Finally, in the data fusion center, the optimal classification results are updated according to the cost function.

5. Conclusions

This article provided a review on machine learning based cooperative spectrum sensing algorithms in cognitive networks from both theoretical and technical perspectives. In particular, this article focused on the cooperative schemes in three machine learning algorithms, including support vector machine, Convolutional Neural Network, and deep reinforcement learning. It is worth pointing out there are several aspects in need of improving for CSS algorithms.

1) The SVM classifier training time of energy vectors is the least one. Thus, the SVM model is suit for CSS if we need a short training time.

2) The Region of Convergence (ROC) of deep reinforcement learning CSS is the best one, and the ROC of SVM-CSS is the worst one.

3) The training time of three machine learning CSS algorithms is relate to the frequency quality. The lower frequency quality will lead to the more training time.

Acknowledgments

Research supported in part by grant for the Scientific Research Program Funded by Shaanxi Provincial Education Department (18JK1005), National Natural Science Foundation of China (61703329), Yulin
Science and Technology Plan Project (CXY-2020-037), Xi’an Science and Technology Plan Project (2020KJRC0068).

References
[1] K.M. Thilina, K.W. Choi, N. Saquib, and E. Hossain, “Machine learning techniques for cooperative spectrum sensing in cognitive radio networks,” *IEEE J. Sel. Areas Commun.*, 2013, 31(11), pp. 2209–2221.
[2] S. Haykin, “Cognitive radio: brain-empowered wireless communications”, *IEEE J. Sel. Areas Commun.*, 2005, 23 (2), pp. 201–220.
[3] Y. Arjoune, N. Kaabouch, “A comprehensive survey on spectrum sensing in cognitive radio networks: recent advances, new challenges, and future research directions”, *Sensors*, 2019, 19 (126), pp. 1–32.
[4] C.M. Bishop, *Pattern recognition and machine learning*, Springer, USA, 2006.
[5] S. Zhang, Y. Hu, L. Zhang, and Z. Bao, “Novel spectrum sensing and access in cognitive radio networks,” *Sci. China Inf. Sci.*, 2018, 61(8), Art. no. 089302.
[6] F. Azmat, Y. Chen, and N. Stocks. “Analysis of spectrum occupancy using machine learning algorithms,” *IEEE Trans. Vehi. Tech.*, 2016, 65(9), pp. 6853–6860.
[7] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” in *Proc. Adv. Neural Inf. Process. Syst.*, 2012, pp. 1097–1105.
[8] W. Wu, Z. Li, S. Ma, J. Shi, “Performance improvement for machine learning-based cooperative spectrum sensing by feature vector selection”, *IET Com.*, 2020, 14(7), pp. 1081-1089.
[9] B. Liu, M. Huang, J.T. Wang, “Cooperative spectrum sensing via 2-sprt based multiple-model hypothesis testing”, in *Proc. Asian Cont. Conf.*, 2017, pp. 2502–2507.
[10] S. Atapattu, C. Tellambura, H. Jiang, “Energy detection based cooperative spectrum sensing in cognitive radio networks”, *IEEE Trans. Wirel. Commun.*, 2011, 10 (4), pp. 1232–1241.
[11] L. Gahane, P. Sharma, “Performance of improved energy detector with cognitive radio mobility and imperfect-CSI”, *IET Commun.*, 2017, 11 (12), pp. 1857–1863.
[12] I. Sobron, P.S. Diniz, W.A. Martins, et al., “Energy detection technique for adaptive spectrum sensing’, *IEEE Trans. Commun.*, 2015, 63 (3), pp. 617–627.
[13] R. Sarikhani, F. Keynia, “Cooperative Spectrum Sensing Meets Machine Learning: Deep Reinforcement Learning Approach”, *IEEE Commun. Lett.*, 2020, 24 (7), pp. 1459–1462.
[14] W. Lee, M. Kim, and D.-H. Cho, “Deep power control: Transmit power control scheme based on convolutional neural network,” *IEEE Commun. Lett.*, 2018, 22(6), pp. 1276–1279.
[15] M. Kim, N.-I. Kim, W. Lee, and D.-H. Cho, “Deep learning-aided SCMA,” *IEEE Commun. Lett.*, 2018, 22(4), pp. 720–723.