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AI-Enhanced Cooperative Spectrum Sensing for Non-Orthogonal Multiple Access

Zhenjiang Shi, Wei Gao, Shangwei Zhang, Jiajia Liu, and Nei Kato

Abstract

Many state-of-the-art techniques are leveraged to improve spectral efficiency, of which cognitive radio and multiple access are the most promising ones. In cognitive radio communications, spectrum sensing is the most fundamental part, whose accuracy has a significant impact on spectrum utilization. Furthermore, due to the complex radio environment, multiple-user CSS has been proposed as a refined solution. NOMA, as an essential technique in 5G, holds great promise in improving spectral efficiency and carrying massive connectivity. In this article, we propose a novel CSS framework for NOMA to further improve the spectral efficiency. Considering the complicated physical layer implementations of NOMA, we introduce an AI based solution to cooperatively sense the spectrum with a nice accuracy rate and acceptable complexity. Numerical results validate the effectiveness of our proposed solution.

Introduction

With the emerging era of Internet of everything, a series of novel applications, including but not limited to autonomous driving, smart city and augmented reality, have been posing unprecedented requirements for bandwidth, latency and connectivity in wireless networks. More than 50 billion Internet of Things devices will be connected to the Internet by 2020 [1], so the scarcity of spectrum resources is becoming more and more prominent. How to improve spectral efficiency to meet such requirements has been intensively investigated by the academic and industrial communities.

On the one hand, a variety of multiple access techniques have been designed as cellular networks evolve. Previous multiple access techniques, according to radio resource allocation criteria, can be mainly divided into orthogonal multiple access (OMA) in conventional cellular networks and NOMA in 5G. The OMA is implemented by assigning orthogonal resources in frequency, time or code domain to different users, in which all users can simultaneously access the cellular infrastructures without multi-user interference. Instead, NOMA allows the same resources to carry different users at the same time, and shows excellent performances on both spectral efficiency and massive connectivity [2], which makes it an essential access technology in 5G [3]. However, in either case, users are in a relatively passive state, and base stations (BSs) play an important role in resource allocation which may limit the reuse of precious spectrum.

On the other hand, the Federal Communications Commission has pointed out that despite the exponential growth in demand for radio spectrum, the vast majority of licensed spectrum is underutilized. Therefore, cognitive radio communication has been accordingly proposed to further boost spectral efficiency, where the users may have more initiatives. In cognitive radio communication, each user is endowed with cognitive ability to detect the spectral holes by perceiving the surrounding radio environment, and the ability to access the idle licensed frequency band opportunistically. Generally, cognitive communication includes two steps, that is, continuous spectrum sensing and dynamic spectrum access, while the former is the premise of the latter [4]. Accurate sensing is able to help users correctly occupy the spectral holes, otherwise low spectral efficiency or multi-user interference will appear. Hence, how to accurately and effectively detect the channel states has attracted much research effort. Furthermore, due to the complex shadowing and fading of radio environments, sensing by a single user becomes unreliable. Thus, CSS is proposed to tackle this challenge, which utilizes multiple users to cooperatively perceive the channel states and comprehensively make decisions [5].

In light of the significant effects of NOMA and CSS on improving spectral efficiency, we propose a novel CSS framework for NOMA to further boost spectrum utilization. Since the complicated physical layer implementation of NOMA makes available CSS solutions unsuitable (if not impossible) to sense the channel states, AI is introduced in our framework to achieve higher sensing accuracy with much lower computational complexity. In particular, we present a new CSS framework for NOMA as well as an efficient AI-enhanced solution, being able to effectively address the complex descriptions and implementations of NOMA.

The rest of this article is organized as follows. First, the preliminaries about NOMA, spectrum sensing and AI are introduced. Next, we present the framework of CSS for NOMA, and develop the AI-enhanced solution after analyzing the detailed technical challenges. Then we present extensive numerical results for performance illustration. Finally, we conclude the article.

Zhenjiang Shi is with Xidian University; Wei Gao is with Huazhong University of Science and Technology; Shangwei Zhang and Jiajia Liu are with Northwestern Polytechnical University, Xi'an, China; Nei Kato is with Tohoku University.

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Recently, AI has been in the spotlight. AI-enhanced applications, such as autonomous driving, face recognition, natural language processing, and intelligent medicine, have sprung up. AI can be roughly divided into machine learning and deep learning, whose model complexity, model generalization ability, training data requirements and training time are totally different.

Preliminaries

Advanced Radio Resource Management in Wireless Communications

Multiple Access in Cellular Networks: Multiple access enables several users to share available resources in the most effective manner. From the historical view, orthogonality is an important criterion to efficiently share available spectral resources. Non-orthogonality, which is another novel criterion in 5G networks, is also showing its powerful ability in improving spectral efficiency and massive connectivity by serving multiple users in the same time-frequency resource [2].

The mainstream of NOMA includes power-domain NOMA and code-domain NOMA. The first one serves multiple users which employ different transmission powers in the same time-frequency resource, while the second designs a sparse codebook for each user whose data is then mapped accordingly based on the code-book. As NOMA enables users to transmit in a superimposed manner, it can provide a much larger sum rate than traditional OMA [6], especially when applied together with multiple-input multiple-output communication systems [7].

There are already some pioneering works. As an important variation of power-domain NOMA, a scheme combining power-domain NOMA with cognitive radio was proposed in [6] where NOMA was treated as a special case of cognitive radio, and a power allocation strategy was designed to meet the predefined quality of service requirements. Closed-form analytical results were provided to prove the effectiveness of cooperative transmission in down-link NOMA [8], and the authors showed that better performance can be obtained with more relaying users.

Spectrum Sensing in Cognitive Radio Communications: In cognitive radio communications, a primary user (PU) possesses a high priority, while a secondary user (SU) who opportunistically accesses channel resources through spectrum sensing possesses a low priority. Compared with non-cooperative spectrum sensing, CSS is able to enhance the sensing performance, in which SUs collaborate with each other to sense spectrum and find spectral holes, especially in complex shadowing and fading radio environments.

There are different kinds of detection methods developed for CSS, such as energy detection, matched filter detection, and cyclostationary detection. To be specific, an optimally normalized energy detection-based CSS scheme was proposed in [9], and first-order correlation of the perceived signal samples was introduced in [10] to improve the detection performance. In comparison with mainstream energy detection, matched filter detection requires more prior knowledge, while cyclostationary detection has the highest sensing accuracy and the greatest computational complexity of the three.

As for CSS fusion schemes, there are hard and soft fusion schemes depending on whether a single SU makes a decision. In hard fusion schemes, which usually apply a voting based fusion strategy, each SU independently makes a decision on channel states according to the perceived signal. Each SU then transmits the decision to a fusion center, and the fusion center makes a final decision by voting. Opposite to hard fusion, each SU is only responsible for perceiving signal which needs to be transmitted to the fusion center in soft fusion schemes, then the fusion center makes a final decision. Hard and a soft fusion schemes based on hidden bivariate Markov models were proposed in [5], and a linear soft fusion strategy with a heuristic optimization algorithm based on modified deflection coefficient was proposed in [4]. Generally, soft fusion although with lower computation efficiency, has higher sensing accuracy than hard fusion. In addition, from the perspective of energy consumption, soft fusion is more suitable than hard fusion when performing environmental monitoring [11].

Note that due to the complexity of physical layer implementation in NOMA, such as complex receiver and complicated power allocation, the applications of NOMA are limited. Many previous approaches have considered the problem of CSS for traditional OMA. In this article, we propose a novel CSS framework for NOMA to further improve spectral efficiency, which to our best knowledge has not been proposed yet. AI technology is applied to tackle these challenges in complex physical layer of NOMA.

Artificial Intelligence

Recently, AI has been in the spotlight. AI-enhanced applications, such as autonomous driving, face recognition, natural language processing, and intelligent medicine, have sprung up. AI can be roughly divided into machine learning and deep learning, whose model complexity, model generalization ability, training data requirements and training time are totally different. By contrast, machine learning requires less data and training time than deep learning, but its generalization ability is relatively weaker due to the naive model.

The AI-enhanced solutions of CSS for OMA based on convolutional neural networks [12], K-means, Gaussian mixture model and K-nearest-neighbor [13] were proposed, and great performance improvement has been observed there. The authors in [14] provided a support vector machine (SVM) based CSS solution, which utilizes the user grouping method to reduce cooperation overhead and boost detection performance. Meanwhile, the idea of eliminating abnormal and interfering data from the overall data is also applied in [15].

In light of the complex physical layer of NOMA, many simulation optimization problems are non-convex and difficult to solve. Therefore, deep learning and unsupervised learning have been introduced to enhance the performance in multi-carrier NOMA and millimeter-wave NOMA.

Based on these, AI-enhanced CSS is a promising solution for less prior information requirements and higher sensing accuracy. Although deep learning has very good classification ability for ultra-high-dimensional models, its computational complexity is extremely high. Accordingly, we propose in this article a solution based on directed acyclic graph-support vector machine (DAG-SVM) with low computational complexity and high sensing accuracy.

CSS for NOMA and AI-Enhanced Solution

System Framework

As shown in Fig. 1, we consider an uplink communication of a cognitive radio system, in which there exist two PUs and M SUs, denoted by $\{PU_1, PU_2\}$ and $\{SU_1, SU_2, \cdots, SU_M\}$, respectively. The spectrum resources are allocated to the PUs according to power domain NOMA, that is, the signals of PUs are transmitted simultaneously with different transmission powers in the same channel. Without loss of generality, the PU_1 with poor channel condition and the PU_2 with good channel condition are assumed in our framework. In addition, the PU_1 is allocated with high power as the strong user and the PU_2 is allocated with low power as the weak user. Each PU has two states, active or idle. Therefore, four channel states can be obtained with two PUs, that is, both PUs are active or idle, and one is active and the other is idle. According to power-domain NOMA, if any PU is idle, the channel is available to be reallocated, otherwise it is not allowed.

The procedures of CSS for NOMA are described in Fig. 2. Supposing that the SU_i needs to transmit signal to a BS. It first sends a request to the fusion center for collaborating with the other SUs, then the fusion center instructs the other SUs in the coverage area to perceive the current radio environment. In the second step, each SU sends the perception information to the fusion center. At last, the fusion center decides the channel states and passes it back to SU_i. As long as any PU is idle, SU_i can access the channel and transmit signal by adjusting its own parameters (e.g., when PU_1 is idle and PU_2 is active, the SU_i will use high power, and transmit signal together with PU_2). When all PUs are active, SU_i will retreat for a period before the next perception.

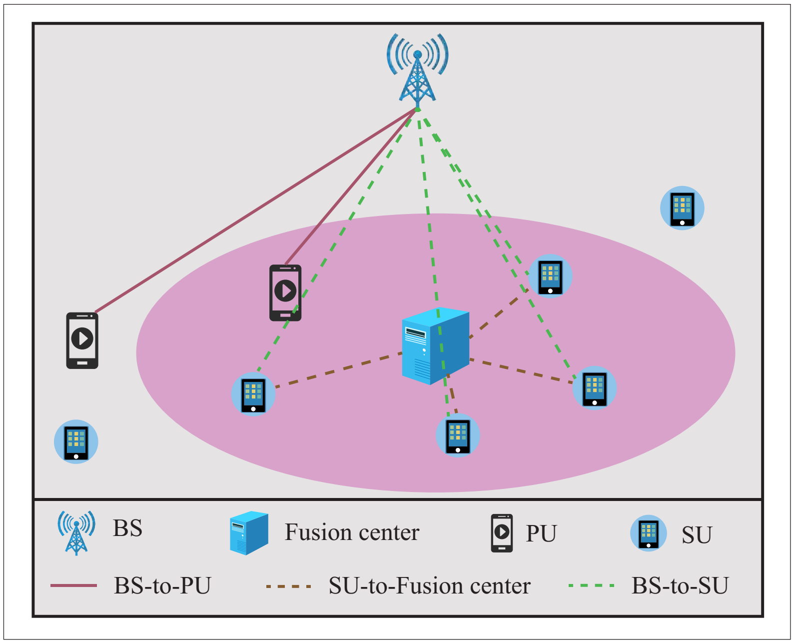

FIGURE 1. The framework of cooperative spectrum sensing for NOMA.

CSS for NOMA

In the proposed framework, we denote by N the rate of oversampling the channel. The k^{th} sample of the SU_i perceived at a time slot can be denoted as

$$\begin{cases} H_{00}: x_i(k) = n_i(k) \\ H_{01}: x_i(k) = \sqrt{\Omega_2} h_{2,i} S_2(k) + n_i(k) \\ H_{10}: x_i(k) = \sqrt{\Omega_1} h_{1,i} S_1(k) + n_i(k) \\ H_{11}: x_i(k) = \sqrt{\Omega_1} h_{1,i} S_1(k) + \sqrt{\Omega_2} h_{2,i} S_2(k) + n_i(k) \end{cases}, \quad (1)$$

where H_{00}, H_{01}, H_{10}, H_{11} denote four possible channel states. S and Ω are the transmitted signals and the power coefficients of PUs, respectively. We define the additive white Gaussian noise n as the first channel noise. Furthermore, the signal undergoes transmission of the Rayleigh channel, and the channel gain h is assumed to be constant in each time slot.

The N samples perceived by SU_i at the l^{th} time slot are summed to get a statistic u_i^l which can be obtained by $u_i^l = \Sigma_{k=1}^N |x_i(k)|^2$, $i = 1, 2, \ldots, M$. According to the central limit theorem, u_i^l is approximately subject to normal distribution when the sample rate N is large enough. Then u_i^l will be sent to the fusion center through a control channel, and the signal from SU_i received by the fusion center can be represented as $y_i^l = u_i^l + v_i$. v_i is the zero-mean Gaussian channel thermal noise with variance δ_i^2, which is defined as the second channel noise. $\{y_i^l\}$, $i = 1, 2, \ldots, M$ from different SUs together constitute the training data of the l^{th} time slot. We obtain an $L \times M$ training data set by collecting over L time slots as $\mathbf{Y} = [\mathbf{Y}^1, \mathbf{Y}^2, \ldots, \mathbf{Y}^L]^T$, where $\mathbf{Y}^l$ is a column vector. $\mathbf{Y}^l = [y_1^l, y_2^l, \cdots, y_M^l]^T$ denotes the training data received by the fusion center from all SUs in the l^{th} time slot. Finally, the fusion center needs to decide in which state the channel is according to the training data $\mathbf{Y}$. Obviously, the decision progress can be formulated as a classification problem. Each SU transmits the processed perception signal as an input to the fusion center, and then the fusion center makes a judgment.

AI-Enhanced Solution

In a traditional OMA mechanism, CSS needs only to judge whether the channel is occupied, and as long as any user occupies it, other cognitive users are not allowed to transmit in this channel. However, in advanced NOMA, more than one user is allowed to transmit simultaneously in the same time-frequency resource, and the cognitive user can transmit when any PU is idle. Obviously, NOMA can achieve much higher spectral efficiency than conventional OMA, but as the number of simultaneous transmission users increases, the number of channel states increases exponentially. For example, if Q users are allowed to transmit together in a channel, there are 2^Q different combinations of channel states. Thus, compared with the OMA mechanism, NOMA poses huge challenges to CSS.

In addition, when a traditional statistical model is applied to solve the problem of CSS for NOMA, the joint probability distribution function of the hypothesis test will become extremely complicated, and the computational complexity will also become tremendously high. Therefore, we need to consider more efficient techniques to tackle these challenges with acceptable sensing accuracy. As an excellent supervised learning algorithm, SVM shows good generalization ability and prediction performance on solving complex non-lin-

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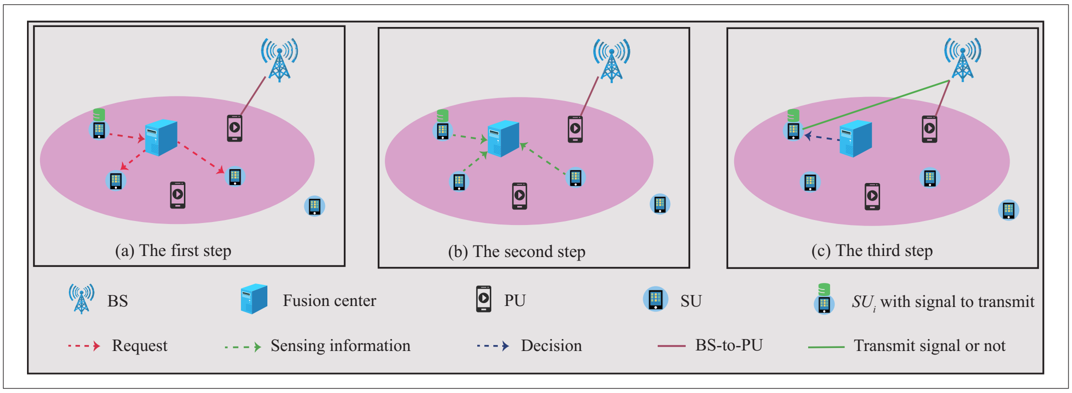

FIGURE 2. The procedures of CSS for NOMA: a) The SU_i who needs to transmit signal sends a request to fusion center, and the fusion center instructs all SUs in its coverage area to assist the SU_i; b) Each SU perceives current radio environment and sends the results to the fusion center; c) The fusion center makes a decision and informs the SU_i, then the SU_i decides to transmit or not.

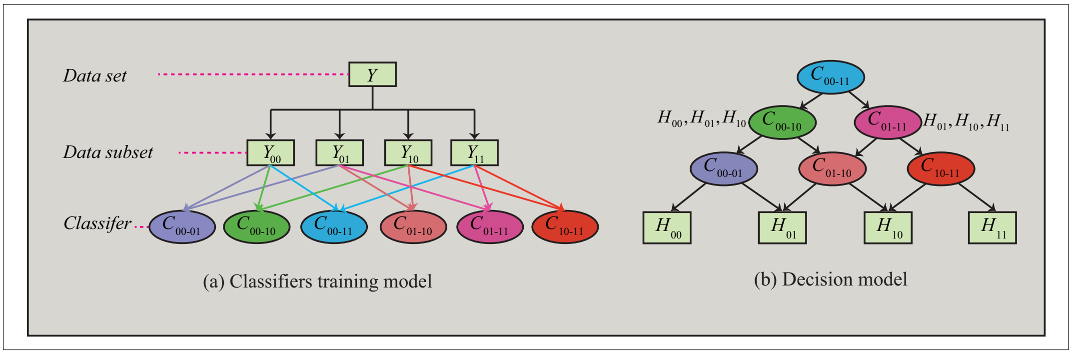

FIGURE 3. A four-category sensing model based on DAG-SVM.

ear problems with small sample data as well as high dimensionality. The original data is mapped to high-dimensional space from low-dimensional space through kernel function to make a linear inseparable problem become linear separable. It will greatly improve the prediction performance. At the same time, since SVM only uses support vectors to make a prediction, it can tremendously reduce the complexity of prediction. However, SVM is a typical binary classifier which is not applicable to the multi-classification problem, so a variation of SVM named DAG-SVM is applied in our proposed solution.

DAG-SVM is a multi-classifier and one-versus-one based. For a P-classification problem, DAG-SVM constructs $P(P - 1)/2$ classifiers, and each classifier can distinguish a pair of classes from the P classes. The training data set is divided into P data subsets according to the label, and data subsets are combined in pairs to train these classifiers as shown in Fig. 3a. When a SU needs to sense spectrum, the fusion center judges along a branch of the model to obtain the final decision on CSS as shown in Fig. 3b. Therefore, DAG-SVM is able to achieve accurate CSS with acceptable computational complexity for NOMA.

According to the analysis above, Fig. 3 shows a four-category sensing model of CSS for NOMA when there are two PUs using one channel. The training stage of classifiers is illustrated in Fig. 3a. At the beginning, since the channel has four states, the training data $\mathbf{Y}$ is divided into four subsets, namely $\mathbf{Y}_{00}$, $\mathbf{Y}_{01}$, $\mathbf{Y}_{10}$ and $\mathbf{Y}_{11}$. We label the subsets according to the energy of perceived signals in subscripts, and the subscripts also denote the states of the channel. Afterwards, any pair of subsets are combined to train a classifier by using SVM with radial basis kernel function (RBF). We adopt the grid search method to search for the optimal parameters (i.e., punishment coefficient C and RBF parameter γ) for each classifier. Fig. 3b shows the prediction stage based on DAG-SVM. When an unlabeled data needs to be predicted, the model first uses the classifier $C_{00\text{-}11}$ at the root node of the decision model to distinguish it. The classification results (H_{00} or H_{11}) reveal the closeness between the data and the candidate prediction results ($\{H_{00}, H_{01}, H_{10}\}$ or $\{H_{01}, H_{10}, H_{11}\}$). The final decision is obtained by the classifiers along the selected branch.

From the procedure we can see that if the previous classifier is misclassified, the follow-up classifiers cannot correct the error since the true class does not appear in latter classifiers. Thus, we always select the classifier with the largest space in the remaining classes as the current node. Through this demonstration, when the number of classes is P, only $P - 1$ judgments are needed to obtain the final decision result, so the effectiveness of CSS can be guaranteed.

NUMERICAL RESULTS

In this section, we conduct intensive performance evaluation for the proposed DAG-SVM based solution. In particular, we investigate the impacts of the number of SUs, training data volume and power allocation, on the sensing accuracy. The variances of the first channel noise are randomly assigned, while the second channel noise variances are set as $\delta_i^2 = 0.5$, i = 1, 2, ⋯, M. The training and test data are obtained according to the system model. 40,000 pieces of data are used to test the sensing accuracy of the proposed solution. The simulation is realized by MATLAB R2018b version and executed on a workstation with an Intel Pentium CPU and 8 GB RAM.

Sensing Accuracy vs. Number of SUs

The DAG-SVM model is trained with configurations of four different numbers of SUs. In this simulation, the power coefficients Ω_1 and Ω_2 are set to be 0.7 and 0.3, respectively. Sensing accuracy under different numbers of SUs is shown in Fig. 4, where the training data size is selected as 400. The sensing accuracy increases monotonically with the number of SUs, reaching 97.10 percent when $M = 20$. It conforms to a common intuition that our DAG-SVM model can solve the CSS problem for NOMA with acceptable accuracy when the number of SUs is sufficiently large. Note further that the model efficiency actually closely relates to the size of the training data volume, as illustrated later.

Sensing Accuracy vs. Training Data Volume

The relationship between sensing accuracy and training data volume is illustrated in Fig. 5, where the power coefficients Ω_1 and Ω_2 are set to be 0.7 and 0.3, respectively. It is interesting to observe that for the setting of $M = 20$, the sensing accuracy drops significantly when the size of the training data is less than 200. This is because as the number of SUs increases, more training data is required to find the separation plane and ensure the sensing accuracy. The lack of training data leads to a performance degradation, namely the "under-fitting." Such observation suggests that given the value of M, that is, the number of SUs, a certain amount of training data is required in order for the DAG-SVM to get satisfactory sensing accuracy.

Furthermore, we can see from Fig. 5 that for all four settings of M, the convergent sensing accuracy will be obtained when the training data size is more than 400. In comparison with the formidable amount of training data size required for deep learning, our DAG-SVM model is able to obtain nice sensing accuracy even with a small size of training data.

Sensing Accuracy vs. Power Allocation

The influences of power allocation on sensing accuracy are shown in Fig. 6. The power coefficient of PU_2 satisfies $\Omega_2 = 1 - \Omega_1$. From the line graph (upper) of Fig. 6, it can be clearly observed that as the power coefficient Ω_1 of PU_1 increases, the overall sensing accuracy will rise first and then decrease. The bar chart (bottom) of Fig. 6 reveals the reasons for the changes of overall sensing accuracy. When the power coefficients change, among the six sub-classifiers, the sensing accuracy of sub-classifiers $C_{00\text{-}01}$, $C_{01\text{-}10}$, $C_{10\text{-}11}$ will be significantly affected.

Specifically, for sub-classifiers $C_{00\text{-}01}$, $C_{10\text{-}11}$, as Ω_1 increases, the signal energy gap between the two channel states becomes smaller, resulting in a lower sensing accuracy for either sub-classifier. However, for sub-classifier $C_{01\text{-}10}$, the perceived energy difference of the two channel states, namely H_{01} and H_{10}, becomes greater as Ω_1 rises, consequently its sensing accuracy increases.

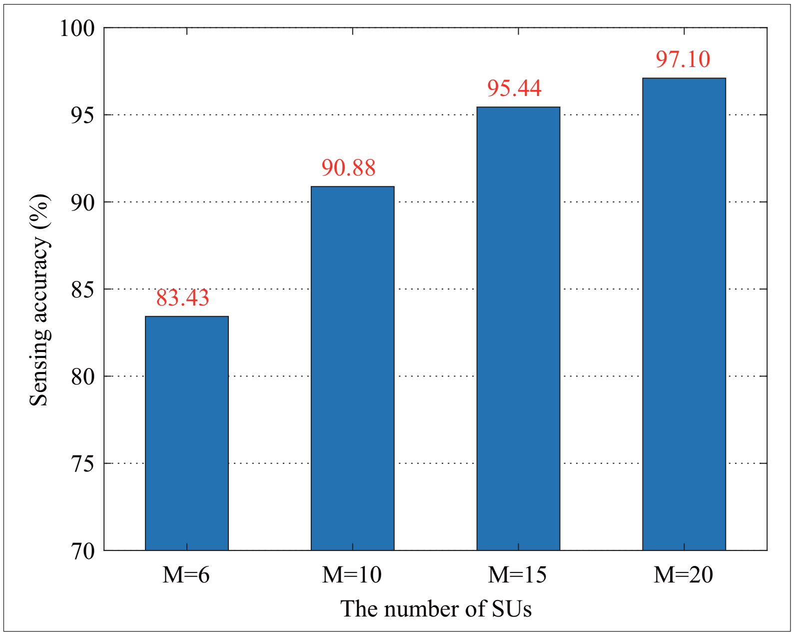

FIGURE 4. Sensing accuracy versus the number of SUs.

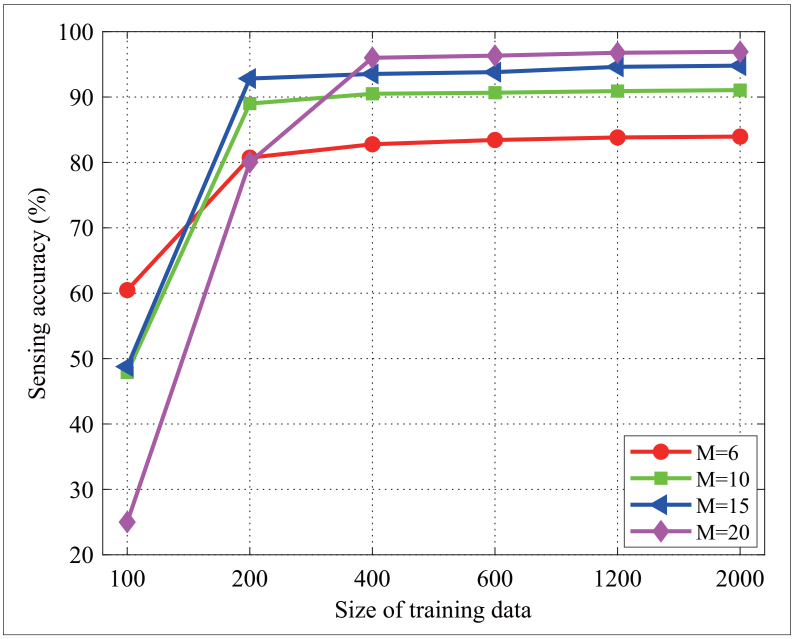

FIGURE 5. Sensing accuracy versus training data volume with different numbers of SUs.

Discussions

In this section, we will discuss the overhead, effectiveness, portability and scalability of the proposed solution.

Overhead: In cognitive radio networks, whether the fusion center is an independent component or one of the SUs plays the role of fusion center, CSS requires SUs to communicate with the fusion center. Compared with cellular networks, cognitive radio networks add the overhead between SUs and the fusion center, but the SUs no longer need to request the BS to allocate resources for them, thus reducing the overhead between the SUs and the BS. On the other hand, both CSS for OMA and CSS for NOMA require SUs to communicate with the fusion center, but the latter can achieve higher spectral efficiency.

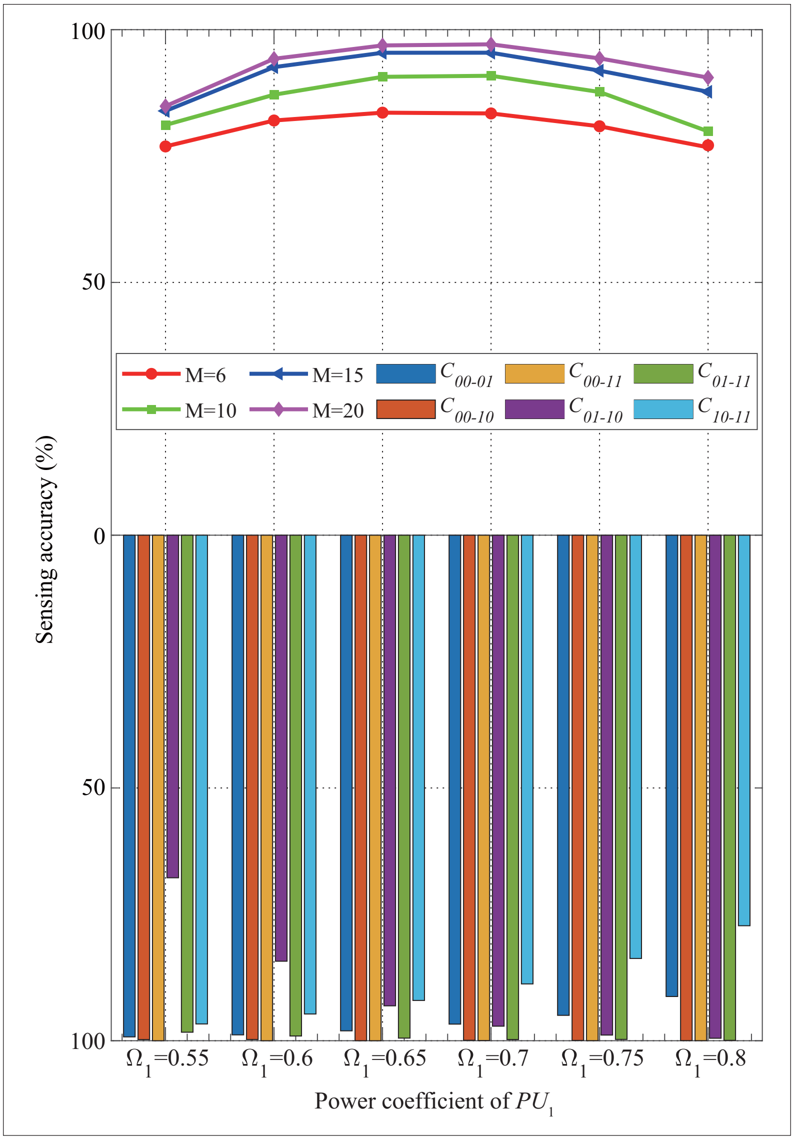

FIGURE 6. Sensing accuracy with different settings of PU_1 power coefficient.

Effectiveness: The effectiveness of the DAG-SVM based solution can be corroborated with the computational complexity in the training stage and the computation efficiency in the prediction stage. In the training stage, it is difficult to accurately describe the computational complexity due to the random learning process of the AI-enhanced solution, so the data volume required for the training model is used to represent the computational complexity. Compared to deep learning models which typically require large amounts of data, the proposed DAG-SVM based model requires only a few hundred pieces of data to be well trained. Thus, a fusion center with limited capability is fully capable of the training task. As for the prediction stage, this model only adopts support vectors to make a judgment, and it takes no more than 1ms on our experiment platform. Considering the training data volume and decision time, our proposed solution holds great promise in application toward CSS for NOMA.

Portability and Scalability: In this article, we only focus on a simple system framework with two PUs and a single channel. Through the above discussions of effectiveness in the training stage and the prediction stage, we can easily extend the problem to a multiple channels scenario and multiple PUs scenario in the practical NOMA framework, by repeating our proposed solution in each channel and extending more possible channel states, respectively. Furthermore, the proposed solution can also be applied to ad-hoc wireless networks inspired by cognitive radio, where each SU can be used as a fusion center.

Conclusions

As the first attempt, we have presented a new framework for achieving CSS in NOMA, and proposed a DAG-SVM based solution. As validated by extensive numerical results, our solution is able to achieve very efficient and accurate spectrum sensing by requiring only several hundreds of training data and less than 1ms prediction time, which possess obvious advantages over traditional CSS schemes and deep learning based solutions. Interestingly, we find that there exists an optimal setting of power allocation between the two PUs, at which the maximum sensing accuracy rate is achieved, for all different settings of M, that is, the number of SUs.

Acknowledgments

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Biographies

Zhenjiang Shi [S'18] received his B.S. degree in information and computing science from Shanxi University in 2018. He is pursuing his Ph.D. degree in the School of Cyber Engineering, Xidian University. His research interests cover cognitive radio, AI and NOMA.

Wei Gao received his B.S. degree in communication engineering from Huazhong University of Science and Technology in 2014. He is pursuing his Ph.D. degree in the School of Electronic Information and Communications, Huazhong University of Science and Technology, and working with the National Mobile Communications Research Laboratory, Southeast University. His research interests cover 5G, radio resource allocation and massive MIMO.

Shangwei Zhang [S'15, M'19] received his M.S. and Ph.D. degrees in computer science and technology from Xidian University in 2011, and 2019, respectively. He is currently an associate professor with the School of Cybersecurity, Northwestern Polytechnical University. His research interests cover a wide range of areas including wireless and mobile ad hoc networks, space-air-ground integrated networks, MIMO, Internet of Things, and 5G.

Jiajia Liu [S'11, M'12, SM'15] is currently a full professor at the School of Cybersecurity, Northwestern Polytechnical University. His research interests cover wireless mobile communications, FiWi, IoT, and more. He has published more than 130 peer-reviewed papers in many prestigious IEEE journals and conferences, and currently serves as an associate editor for *IEEE Transactions on Wireless Communications* and *IEEE Transactions on Vehicular Technology*, an editor for *IEEE Network*, and a guest editor of IEEE TETC and the *IEEE Internet of Things Journal*. He is a Distinguished Lecturer of IEEE ComSoc.

Nei Kato [A'03, M'04, SM'05, F'13] is a full professor (Deputy Dean) with the Graduate School of Information Sciences (GSIS) and the Director of the Research Organization of Electrical Communication (ROEC), Tohoku University, Japan. He has been engaged in research on computer networking, wireless mobile communications, satellite communications, ad hoc and sensor and mesh networks, smart grid, AI, IoT, Big Data, and pattern recognition. He has published more than 400 papers in prestigious peer-reviewed journals and conferences. He is the Vice-President (Member and Global Activities) of the IEEE Communications Society (2018-2019); Editor-in-Chief of *IEEE Transactions on Vehicular Technology* (2017-); and the Chair of the IEEE Communications Society Sendai Chapter. He served as the Editor-in-Chief of *IEEE Network Magazine* (2015-2017); a Member-at-Large on the Board of Governors of the IEEE Communications Society (2014-2016); a Vice Chair of the Fellow Committee of the IEEE Computer Society (2016); and a member of the IEEE Communications Society Award Committee (2015-2017). He is a Distinguished Lecturer of the IEEE Communications Society and Vehicular Technology Society. He is also a fellow of The Engineering Academy of Japan and IEICE.