Spectrum Sensing for OFDMA Using Multicarrier Covariance Matrix Aware CNN

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Abstract: We consider spectrum sensing problems in the orthogonal frequency division multiplexing access (OFDMA) cognitive radio scenario, where a secondary user with multiple antennas detects several consecutive subcarriers of an entire OFDM symbol occupied by multiple primary users. Specifically, an OFDM multicarrier covariance matrix convolutional neural network (CNN)-based approach is proposed for simultaneously detecting the occupancy of all OFDM subcarriers, where the multicarrier sample covariance matrix array is specially set as the input of the CNN. The proposed approach can efficiently learn the energy information and correlation information between antennas and between subcarriers to significantly improve the spectrum sensing performance. Numerical results demonstrate that the proposed method has a substantial performance advantage over the state-of-the-art spectrum sensing methods in an OFDMA scenario under the 5G new radio network.

Keywords: cognitive radio; spectrum sensing; OFDMA; deep learning; 5G new radio

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1 Introduction

Spectrum resources are key strategic resources to constructing new competitive advantages in the global information technology, technological innovation, and economic development. The scarce spectrum resources have become an important factor limiting the high speed and large capacity of the 5G networks[1]. The cognitive radio (CR) technology[2], which allows secondary users (SUs) to opportunistically access primary users' (PUs) licensed bands without affecting the communication quality of the PU, has become a reliable method to make efficient use of spectrum resources. Spectrum sensing, as an important part of CR, needs to continuously detect and determine whether the PU occupies the frequency band for communication through spectrum data before SU accesses this frequency band[3]. A large amount of research has been conducted on spectrum sensing both in academia and the industry over recent years[4].

Energy detection (ED)[5] is the commonest and simplest method of spectrum sensing, but it requires prior knowledge of noise energy and its performance is vulnerable to noise uncertainty (NU)[6 – 7]. An eigenvalue-based sensing method[8] was proven to be stable under the influence of NU by using antenna correlation information rather than energy information to perform sensing. Various methods based on eigenvalues, such as the maximum-minimum eigenvalue (MME) detection[8], arithmetic to geometric mean (AGM)[9] detection, mean-to-square extreme eigenvalue (MSEE)[10] detection, maximum eigenvalue-to-arithmetic mean (ME-AM) detection and maximum eigenvalue-to-geometric mean (ME-GM) detection[11 – 12], were proposed to calculate a good test statistic with improved performance, but the performance of these methods varies with different channel models and it is difficult to build an accurate model in the practical wireless environment. To further improve the sensing performance, many spectrum sensing methods based on deep learning (DL)[13] have been proposed, which are motivated by the powerful potential of DL to learn the data-driven features[14]. In Ref. [15], energy information and the statistics of likelihood ratio were treated as the input of the artificial neural network (ANN) to perform spectrum sensing. In Ref. [16], the CNN-based sensing method using a covariance matrix as the input was proposed to obtain the optimal test statistic. Besides the correlation and the energy information, other hidden features like PU's activity pattern could be learned by CNN[17] and the Long Short-Term Memory (LSTM) network[18] to assist spectrum sensing.

Nowadays, most of the 5G wireless communication networks are built under the orthogonal frequency division multiplexing (OFDM) system for high speed transmission of signals

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over broadband wireless channels. OFDM has been adopted in several wireless standards, such as IEEE 802.11, IEEE 802.16, 3GPP-LTE, and LTE-Advanced, and various enhanced OFDM schemes have been developed in the 5G new radio (NR) network. How to efficiently perform spectrum sensing in such broadband scenarios to detect the usage of the idle subcarriers has become a key issue still worth investigating. Most of current researchers like in Refs. [19 – 20] are devoted to exploring how to detect the existence of an entire OFDM symbol, rather than detecting which subcarrier is occupied in the entire OFDM symbol. It is therefore difficult to directly migrate these methods to the wideband multi-user systems. Note that many traditional multiband spectrum sensing methods can be applied to the OFDM access (OFDMA) scenarios. For example, the multiband sensing frameworks based on narrowband ED were proposed in Refs. [21 – 22]. In Ref. [23], eigenvalue-based methods were performed on each subchannel in the OFDMA scenarios. In Ref. [24], a DL-based method was proposed to combine the decisions of all SUs on all subchannels. However, these methods ignore the correlation between subchannels and are vulnerable to interference from the frequency selective channel fading, the diversity of PUs' signal power, and the noise uncertainty in practical 5G wireless communication networks.

We propose a CNN-based spectrum sensing algorithm for an OFDMA system with multiple PUs and a multi-antenna SU, which aims to detect the occupancy of subcarriers in an entire OFDM symbol. Specifically, based on the received OFDM symbols, we utilize a multicarrier covariance matrix array as the input of the proposed CNN, ending up with an OFDM multicarrier covariance matrix-CNN (OMCM-CNN) algorithm. The proposed OMCM-CNN algorithm enjoys the following features.

1) In addition to the energy information and antenna correlation information on each subcarrier in the OFDMA system, it can simultaneously learn the correlation information between subcarriers to assist spectrum sensing.

2) It can simultaneously detect the occupancy of all subcarriers in an entire OFDM symbol, while most researchers concern only the detection of the whole OFDM symbol but not the busy state of subcarriers in an OFDM symbol.

3) It can achieve satisfactory spectrum sensing accuracy over the existing methods and its performance is evaluated by simulations under the 5G NR frame structure where the frequency selective channel fading, the diversity of PUs' signal power, and the noise uncertainty are considered.

2 System Model

We consider an OFDMA CR system with N_s subcarriers, K PUs, and an SU, where each PU is equipped with a single antenna and the SU has M antennas to receive the entire OFDM symbols emitted by PUs. SU aims to detect which subcarriers of the radio frequency spectrum of PUs are occupied or sensed idle, so that the SU can utilize the idle subcarriers for communication. In an OFDMA system, an entire block of frequency bands with multiple sets of subcarriers is assigned to one PU for a period each time. A resource block (RB), which contains N_f consecutive subcarriers in the frequency domain and a slot (N_t OFDM symbols) in the time domain, is a minimum time-frequency resource unit allocated to one PU. Taking N_r RB as a subchannel, the k-th PU selects B_k consecutive subchannels with a random location for communication at each sensing time. In addition to the location of the occupied subchannels, the activity pattern of PUs is assumed to be varied with time. The probability of PU k accessing the subchannels for communication is set to be P_k. Furthermore, the receiving signal-to-noise ratios (SNR) of different PU signals are different because of different locations and transmit powers. For simplicity, we assume that the SNRs are uniformly distributed within $[c - w, c + w]$, where c is the average SNR of all PUs and w is the SNR fluctuation factor. Fig. 1 depicts an example of PUs' occupancy in the OFDMA CR system. To this end, we can model the multiband spectrum sensing problem in OFDMA CR network as a binary hypothesis testing problem on multiple channels, which can be expressed as:

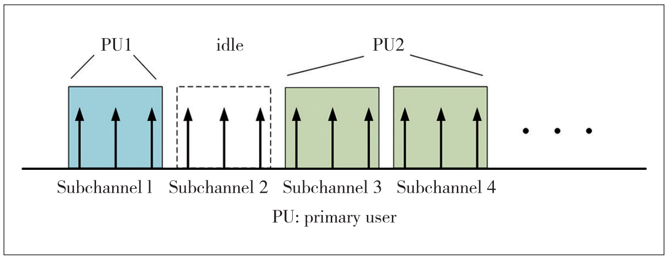
$$\boldsymbol{Y}_b = \begin{cases} \boldsymbol{H}_b \boldsymbol{X}_b + \boldsymbol{W}_b, & H_1 \\ \boldsymbol{W}_b, & H_0 \end{cases}, \tag{1}$$

where $b = 1,\cdots,B$ represents the b-th subchannel and B is the total number of subchannels; $\boldsymbol{Y}_b$ and $\boldsymbol{X}_b$ are the received OFDM symbol and the transmitted OFDM symbol in the frequency domain, respectively; $\boldsymbol{H}_b$ is the channel frequency domain response on subchannel b; H_0 and H_1 represent the binary hypothesis to indicate that subchannel b is idle and occupied, respectively. The popular detector employing signal magnitude information is energy detection[5], which is to detect whether the signal energy on the subchannel is greater than the noise energy threshold.

$$E\left\{\left\| Y_b \right\|^2\right\} \underset{H_0}{\overset{H_1}{\gtrless}} \sigma_W^2. \tag{2}$$

Note that energy detection has the following problems: 1) It requires prior information about the value of noise energy σ_W^2. 2) It relies entirely on energy information for sensing and its detection performance is significantly declined under noise uncertainty. 3) Correlation information between subchannels, such as user occupancy of consecutive subchannels and channel response correlation, is ignored as each subchannel is separately detected. Therefore, we need to jointly detect all subchannels based on the energy information, antenna correlation information, and subchannel correlation information to improve the spectrum sensing performance.

In an OFDM system, the receiver samples the OFDM symbol in the whole frequency band at each time. After sampling and removing the cyclic prefix (CP), we get the received sig-



▲ **Figure 1. PUs' occupancy on an orthogonal frequency division multiplexing (OFDM) symbol**

nal $\boldsymbol{y}(n) = [y_1(n),\cdots,y_M(n)]^{\mathrm{T}}$ in the time domain and $(\cdot)^{\mathrm{T}}$ denotes the transpose operation, which is denoted as:

$$\boldsymbol{y}(n) = \sum_{l=1}^{L}\boldsymbol{h}(l)x(n-l) + \boldsymbol{w}(n), \quad n = 0,\cdots,N_s - 1, \tag{3}$$

where $x(n)$ is the N_s point transmit OFDM symbol, and $\boldsymbol{w}(n)$ is the additive white Gaussian noise (AWGN). In addition, the NU is considered where the actual noise power is changing with time. In the NU scenario, the actual noise power is denoted by $\sigma_\omega^2 = \varepsilon\widehat{\sigma}_\omega^2$, where $\widehat{\sigma}_\omega^2$ is the estimate noise power, ε is the NU factor, and ε (dB) is uniformly distributed within $[-D, D]$. The baseband equivalent channel $\boldsymbol{h}(l) \in \mathbb{C}^M$ ($l = 0,\cdots,L-1$) is the discrete-time impulse response of the channel with L resolvable paths and is assumed to be the multipath frequency-selective fading channel. To model the correlation between antennas, $\boldsymbol{h}(l)$ is modeled as an exponential correlated zero mean Gaussian random vector, with $M \times M$ statistical covariance matrix $\boldsymbol{R}_{h(l)}$ and the (p,q)-th element of $\boldsymbol{R}_{h(l)}$ is defined as $\boldsymbol{R}_{h(l)} = \sigma_h^2(l)\cdot\rho^{|p-q|}$, where $\sigma_h^2(l)$ is the channel gain power at impulse l and $\rho \in (0,1)$ denotes the correlation coefficient. Through N_s point FFT demodulation, the received OFDM signal $\boldsymbol{Y}(n)$ in the frequency domain can be expressed as

$$\boldsymbol{Y}(n) = \frac{1}{\sqrt{N_s}}\sum_{i=1}^{N_s}\boldsymbol{y}(i)e^{-\frac{j2\pi in}{N_s}}. \tag{4}$$

The objective of spectrum sensing in the OFDMA CR system is to detect the occupancy on all B subchannels based on the available $\boldsymbol{Y}(n)$.

3 OFDM Multicarrier Covariance Matrix Aware CNN

We propose an OMCM-CNN based sensing method to solve the multicarrier spectrum sensing problem in the OFDMA CR system, which consists of sampling, preprocessing, offline training, and online sensing, as illustrated in Fig. 2. In the sampling stage, the multi-antenna SU samples the whole OFDM frequency band and performs FFT demodulation to get the OFDM symbol $\boldsymbol{Y}(n)$ of length N_s. Then, the offline labeled dataset, where the occupancy is known in advance and the online (unlabeled) samples are the data we prepare to detect, can be constructed from the multi-antenna system. Next, we preprocess the raw data and transform it into a data form so that significant features can be readily learned via CNN, and then construct the training set for offline training. Finally, we perform spectrum sensing based on the well-trained CNN using the test data to get its occupancy on each subcarrier. In the following, the construction of a multicarrier covariance matrix array based on the OFDM symbol, the structure of the proposed CNN, the offline training module, and the online sensing module will be elaborated in detail respectively.

3.1 OFDM Multicarrier Covariance Matrix Array

At each sensing time, we can get N_{sym} OFDM symbol $\boldsymbol{Y}(n)$, where $n = 0,\cdots,N_s - 1$, to perform sensing. Expanding the vector $\boldsymbol{Y}(n)$ at n from $n = 0$ to $n = N_s - 1$, we obtain

$$\boldsymbol{Y} = \begin{pmatrix} Y_{1,0} & Y_{1,1} & \cdots & Y_{1,N_s-1} \\ Y_{2,0} & Y_{2,1} & \cdots & Y_{2,N_s-1} \\ \vdots & \ddots & \ddots & \vdots \\ Y_{M,0} & Y_{M,1} & \cdots & Y_{M,N_s-1} \end{pmatrix}, \tag{5}$$

where $Y_{m,n}$ denotes the m-th element of $\boldsymbol{Y}(n)$. By splitting $\boldsymbol{Y}$ as per column, the OFDM symbol at subchannel b becomes

$$\boldsymbol{Y}_b = \begin{pmatrix} Y_{1,(b-1)N_c} & Y_{1,(b-1)N_c+1} & \cdots & Y_{1,bN_c-1} \\ Y_{2,(b-1)N_c} & Y_{2,(b-1)N_c+1} & \cdots & Y_{2,bN_c-1} \\ \vdots & \ddots & \ddots & \vdots \\ Y_{M,(b-1)N_c} & Y_{M,(b-1)N_c+1} & \cdots & Y_{M,bN_c-1} \end{pmatrix}, \tag{6}$$

where $N_c = N_f \cdot N_r$ represents the number of subcarriers in a subchannel. At each sensing time, the receiver (i.e., SU) can get N_{sym} OFDM symbol $\boldsymbol{Y}$ and N_{sym} $\boldsymbol{Y}_b$ based on Eq. (5). Then, we can concatenate N_{sym} $\boldsymbol{Y}_b$ in the column to get the observation matrix $\widehat{\boldsymbol{Y}}_b$ on subchannel b.

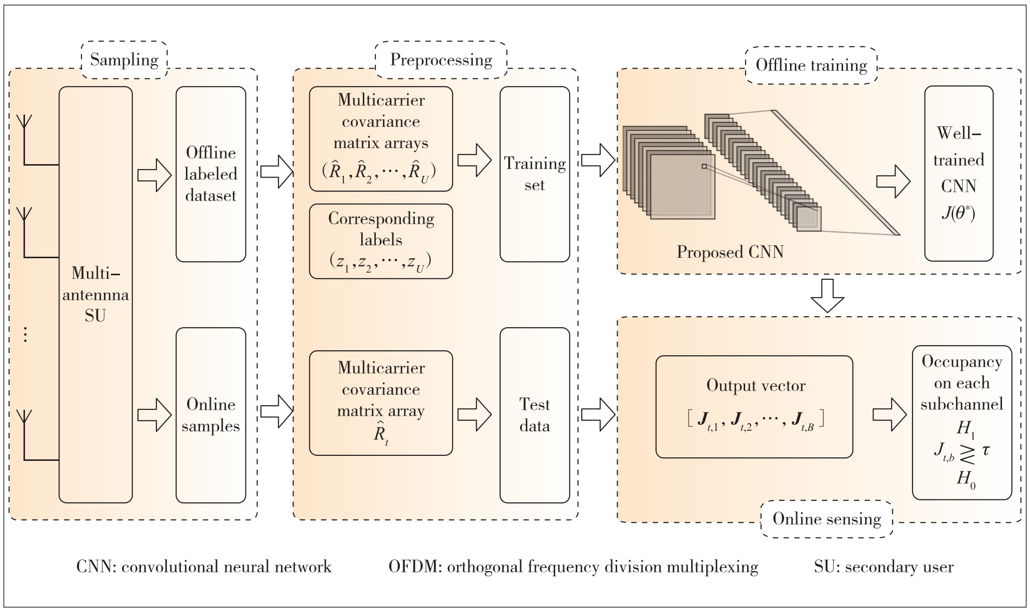
$$\widehat{\boldsymbol{Y}}_b = \left[\boldsymbol{Y}_b^0, \boldsymbol{Y}_b^1, \cdots, \boldsymbol{Y}_b^{N_{\mathrm{sym}}}\right], \tag{7}$$

where $\boldsymbol{Y}_b^{n_{\mathrm{sym}}}$ denotes the n_{sym}-th $\boldsymbol{Y}_b$ within one sensing time.

After obtaining the observation matrix of each subchannel at each sensing time, we need to construct a good CNN model to fit the practical system model by learning appropriate features of the raw data. The statistical sample covariance matrix is considered here, which is calculated as:

$$\boldsymbol{R}_b = \frac{1}{N_0}\widehat{\boldsymbol{Y}}_b\widehat{\boldsymbol{Y}}_b^{\mathrm{H}}, \tag{8}$$

where $N_0 = N_c \cdot N_{\mathrm{sym}}$ stands for the number of observation samples at subchannel b and $(\cdot)^{\mathrm{H}}$ denotes the conjugate transpose operation. The reason for choosing the sample covariance



▲Figure 2. OFDM multicarrier covariance matrix-CNN sensing workflow for spectrum sensing

matrix $\boldsymbol{R}_b$ in Eq. (8) as the input of CNN is that the sample covariance matrix contains not only the energy information of the received signal but also the correlation information between antennas. It has been shown in Ref. [16] that excellent performance of spectrum sensing based on sample covariance matrix could be obtained in the narrowband (single band) sensing scenario. However, such methods which leverage the covariance matrix on each subchannel separately do not utilize the correlation information between the subchannels. To this end, we consider designing a new algorithm that can simultaneously make use of all $\boldsymbol{R}_b$ to detect all subchannels together. Without loss of generality, we concatenate the sample covariance matrices on all subchannels into a big multicarrier covariance matrix array $\widehat{\boldsymbol{R}}$ of $PM \times QM$ size, denoted as

$$\widehat{\boldsymbol{R}} = \begin{pmatrix} \boldsymbol{R}_1 & \boldsymbol{R}_2 & \cdots & \boldsymbol{R}_Q \\ \boldsymbol{R}_{Q+1} & \boldsymbol{R}_{Q+2} & \cdots & \boldsymbol{R}_{2Q} \\ \vdots & \ddots & \ddots & \vdots \\ \boldsymbol{R}_{(P-1)Q+1} & \boldsymbol{R}_{(P-1)Q+2} & \cdots & \boldsymbol{R}_{PQ} \end{pmatrix}, \tag{9}$$

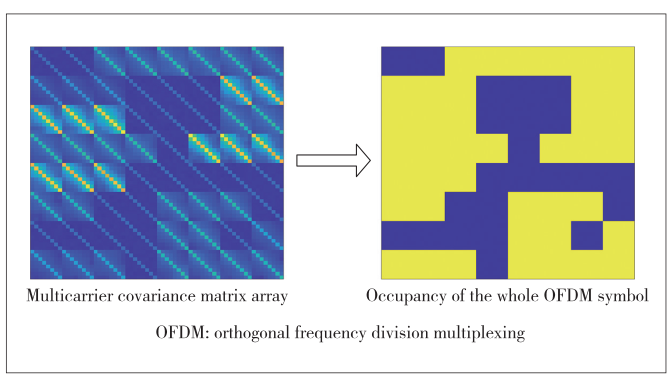
where $PQ = B$. Fig. 3 depicts the characteristics of the multicarrier covariance matrix array example where $M = 8$, $B = 64$, $c = 0$ dB, $w = 2$ dB and $K = 16$. We concatenate the 64 subcarrier covariance matrices into the multicarrier covariance matrix array with $P = 8$ and $Q = 8$. The left subplot is the multicarrier covariance matrix array of the received OFDM symbols. The right subplot is the corresponding OFDM symbol occupancy of the multicarrier covariance matrix array example of given data, where the yellow part represents the occupancy of the received signal and the blue part means it is not occupied or it is idle. By comparison with the two subplots, we see that the multicarrier covariance matrix array in the left subplot can obviously characterize the practical occupancy in the right subplot, and the correlation information between matrix elements and between covariance matrices is obvious to human eyes. Such correlation information between the row and column elements and the specific pattern of the multicarrier covariance matrix array picture can be easily learned by the convolution calculation of CNN, and then yield a decent spectrum sensing performance for online testing.

3.2 CNN Model Selection

In this section, we propose a CNN to detect the occupancy of the OFDMA system based on the OFDM covariance matrix $\widehat{\boldsymbol{R}}$ in Eq. (9). The motivation for choosing CNN includes the following two aspects:

1) CNN is a class of deep neural networks that is widely employed in image classification and recognition and has the powerful potential for extracting hidden features of the matrix-shaped data. Thus, we consider using CNN to learn the energy information and the correlation feature including antenna correlation and subchannel correlation between the row and column elements of $\widehat{\boldsymbol{R}}$, so that we can decide the occupancy on all subchannels based on these distinguishable features.

2) Traditional model-driven methods generally exploit the data features for spectrum sensing based on its models, such as the energies and various expressions of eigenvalues. The performance of model-driven methods depends on the accurate model assumption. However, there does not exist an accurate model for the practical wireless environment. In contrast, CNN is a data-driven method that can obtain the optimal test



▲Figure 3. OFDM multicarrier covariance matrix array and its corresponding subchannel occupancy statistic based on the sensing data without any accurate model assumption for the wireless environments and thus keep a good spectrum sensing performance under different wireless environments.

For the considered OFDMA CR scenario, we propose a CNN with eight layers, which consists of four convolutional layers, three max-pooling layers, and a fully connected layer. Too few convolutional layers will result in a simple CNN structure and cannot effectively fit the relationship between the raw data and the label, while too many convolutional layers will cause the problem of gradient disappearance and gradient explosion. We use four convolutional layers in the proposed CNN based on many empirical attempts, which can avoid the problem of gradient disappearance and gradient explosion, and achieve a good sensing performance. The size of the convolution kernel of all convolution layers is set as 3×3, since the small size of convolution kernel can learn the correlation information between antennas from the convolution calculation of the elements in a single covariance matrix, while learning the correlation between subchannels from the elements in different covariance matrices. As for the activation function, the rectifier linear unit (Relu) is used as the activation function of all convolutional layers, which is to increase the nonlinearity of the proposed CNN model. After the convolution calculation and down-sampling operation in convolutional layers and max-pooling layers, the feature map which contains the occupancy information in the OFDM symbol can be obtained. Then the proposed CNN flattens the feature map into a feature vector and connects it with a fully connected layer to convert the feature vector into the output vector with B elements. Finally, we connect the fully connected layer with the sigmoid function to limit the value range of the output vector within $(0,1)$ and get the final output vector. The sigmoid function is expressed as:

$$S(x) = \frac{1}{1 + e^{-x}}. \tag{10}$$

In this way, the divergence value of the output vector is converted to $(0,1)$, which can be considered as the probability of the occupancy on each subchannel. The hyper-parameter setting is detailed in Section 4.

3.3 Offline Training

After the CNN model selection, we need to optimize the specific parameters of the proposed CNN, which includes the weight and the bias of all convolution kernels and the fully connected layer. Based on the training data set, the objective of the offline training is to fit the relationship between the multicarrier covariance matrix array and the occupancy on all subchannels.

In the offline training stage, numerous labeled OFDM symbols $\boldsymbol{Y}$ in Eq. (5) can be obtained from the offline labeled database, where "label" means that the occupancy of the training OFDM symbol is given. We obtain the training data set with U OFDM multicarrier covariance matrix arrays $\widehat{\boldsymbol{R}}$ and the corresponding labels $\boldsymbol{z}$ via Eqs. (6) – (9). The training data set can be denoted as:

$$\Omega = \left\{\left(\widehat{\boldsymbol{R}}_1, \boldsymbol{z}_1\right),\left(\widehat{\boldsymbol{R}}_2, \boldsymbol{z}_2\right),\cdots,\left(\widehat{\boldsymbol{R}}_U, \boldsymbol{z}_U\right)\right\}, \tag{11}$$

where $\boldsymbol{z}_u \in \{0,1\}^B$ $(u \in \{1,\cdots,U\})$ represents the occupancy of B subchannels in the whole OFDM symbol, "1" means the associated subchannel is occupied and "0" means idle, and U is the total number of the training data set. In this way, we take $\widehat{\boldsymbol{R}}_u$ as the input of CNN and $\boldsymbol{z}_u$ as the label for CNN training. Note that CNN generally does not support the input with complex values. Thus, we should overlap the real and imaginary parts of $\widehat{\boldsymbol{R}}_u$ on the third dimension, and then input this three-dimensional matrix with real values into the CNN. After nonlinear operations of the CNN layers, the output vector, denoted by $\boldsymbol{J}(\boldsymbol{\theta},\widehat{\boldsymbol{R}}_u)$ with B elements can be obtained, where $\boldsymbol{J}(\cdot,\cdot)$ represents the total function of the CNN and $\boldsymbol{\theta}$ denotes the whole CNN model parameters. The purpose of offline training is to make the output of CNN approximate the label data more accurately. To measure the accuracy of the output vector, we use the mean square error criterion, and the loss function is defined as:

$$L(\boldsymbol{\theta}) = \frac{1}{U}\sum_{u=1}^{U}\left\| \boldsymbol{z}_u - \boldsymbol{J}\left(\boldsymbol{\theta},\widehat{\boldsymbol{R}}_u\right)\right\|^2, \tag{12}$$

where $\|\cdot\|^2$ denotes the L_2 norm.

The smaller $L(\boldsymbol{\theta})$ indicates a smaller gap between the output and the label set. To obtain appropriate CNN parameters for online sensing, in the training stage we optimize the loss function $L(\boldsymbol{\theta})$ in Eq. (12) by solving the following minimization problem:

$$\boldsymbol{\theta}^* = \mathrm{argmin}_{\boldsymbol{\theta}} L(\boldsymbol{\theta}). \tag{13}$$

Note that Eq. (13) is non-convex and is generally hard to obtain an analytical solution. Thus, the stochastic gradient descent scheme can be used here to get a sub-optimal solution of Eq. (13). In the simulation, we adopt the optimizer Adam instead of stochastic gradient descent to solve this problem, which is proven to have excellent performance in the deep learning training work[25].

3.4 Online Sensing

After the offline training process, we now use the well-trained CNN with parameter $\boldsymbol{\theta}^*$ to obtain the online sensing results. In the online sensing stage, the SU samples N_0 time-domain received signal sequences $y(n)$ at each sensing time. After data pre-processing via Eqs. (4) – (9), SU can get $\widehat{\boldsymbol{R}}_t$ as the input of the trained CNN to detect the occupancy on all subchannels at sensing time t, where $\widehat{\boldsymbol{R}}_t$ denotes the t-th

OFDM multicarrier covariance matrix array at sensing time t. The output vector can be obtained by the non-linear calculation of the well-trained CNN, denoted as

$$J(\boldsymbol{\theta}^*, \widehat{\boldsymbol{R}}_t) = [J_{t,1}, J_{t,2}, \cdots, J_{t,B}]^{\mathrm{T}}, \tag{14}$$

where $J_{t,b}$ $(b = 1,\cdots,B)$ denotes the b-th output at the t-th sensing time.

Then, we propose a certain coding scheme to transform the output vector into the occupancy vector of all subchannels. As mentioned above, the value of $J_{t,b}$ is limited to $(0,1)$ with the sigmoid function, which can be considered as the probability of the occupancy of subchannel b. Therefore, we can treat $J_{t,b}$ as the test statistic on subchannel b to determine whether subchannel b is occupied or not. Consistent with the decision of traditional sensing algorithms, the occupancy result on subchannel b can be obtained based on the following decision criterion.

$$J_{t,b} \underset{H_0}{\overset{H_1}{\gtrless}} \tau, \tag{15}$$

where τ is the detection threshold, which is determined for the desired probability of false alarm (PFA). We denote the probability of detection (PD) and PFA in our proposed method as follows:

$$P_d = \frac{1}{B}\sum_{b=1}^{B} P\left\{J_{t,b} > \tau | H_1\right\}, \tag{16}$$

$$P_{fa} = \frac{1}{B}\sum_{b=1}^{B} P\left\{J_{t,b} > \tau | H_0\right\}, \tag{17}$$

where P_d and P_{fa} are defined as the averaged probability on all subchannels. Thus, according to the definition of PFA, we can get the estimated value of τ by the the Monte Carlo method. We define $J|H_0$ as the test statistic in the unoccupied situation and $\Omega_{J|H_0}$ as the Monte Carlo dataset of $J|H_0$, where all $J|H_0$ is sorted in descending order. Then, the detection threshold τ with the desired PFA value α is defined as:

$$\tau = \Omega_{J|H_0}\left(\lfloor \alpha U_J \rfloor\right), \tag{18}$$

where $\lfloor . \rfloor$ represents the round down symbol, $\Omega_{J|H_0}(u)$ denotes the u-th elements of $\Omega_{J|H_0}$, and U_J represents the size of the dataset that indicates the number of Monte Carlo realizations.

3.5 Computational Complexity Analysis

We now discuss the computational complexity of the proposed OMCM-CNN method with a comparison of the traditional model-driven methods including energy detection[5] and the Eigenvalue-based methods[8 – 12]. The specific complexity analysis of respective algorithms is given in Table 1, where "×" means that the corresponding method does not need any computational operation. For the energy detection method, $O(BMN)$ denotes the complexity of calculating the energy information of B subchannels. For the eigenvalue-based methods, $O\left(BM^2N\right)$ denotes the complexity of calculating the covariance matrix of B subchannels from the observation matrix and $O\left(BM^3\right)$ is the complexity of the eigenvalue decomposition of B covariance matrices. The computation of OMCM-CNN comes from the offline training stage and the online sensing stage. For OMCM-CNN, $O\left(BM^2N + B\right)$ denotes the complexity of calculating B subband covariance matrices and converting them into the multicarrier covariance matrix array in the preprocessing stage; $O\left(\sum_{l=1}^{D} n_{l-1} s_l^2 n_l m_l^2\right)$ denotes the complexity of obtaining the output vector from the well-trained CNN, where D, s_l, n_l, m_l, N_t, and N_e denote the number of CNN layers, the spatial size of the convolution kernel of the l-th layer, the number of channels of the l-th layer, the spatial size of the output feature map, the numbers of training examples, and the number of epochs in the offline training stage, respectively. In summary, the main computational complexity of the proposed OMCM-CNN algorithm comes from the offline training stage, which needs a relatively high computational complexity to construct the well-trained CNN model. However, the sensing efficiency depends on the computational complexity of online sensing, which aims to get the test statistics directly based on the well-trained CNN model. After the training stage, the complexity of OMCM-CNN in online sensing is greatly reduced, even lower than the complexity of eigenvalue-based methods. That is to say, the proposed method can avoid the computation of eigenvalue decomposition and directly calculate the test statistic based on the well-trained CNN network parameters.

▼Table 1. Computational complexity of respective algorithms

Algorithms	Online Sensing	Offline Training
Energy detection[5]	$O(BMN)$	×
Eigenvalue-based methods[8 – 12]	$O\left(BM^2N + BM^3\right)$	×
OMCM-CNN	$O\left(BM^2N + B\right) + O\left(\sum_{l=1}^{D} n_{l-1} s_l^2 n_l m_l^2\right)$	$O\left(N_t N_e\left(BM^2N + B\right)\right) + O\left(N_t N_e \sum_{l=1}^{D} n_{l-1} s_l^2 n_l m_l^2\right)$

OMCM-CNN: OFDM multicarrier covariance matrix-convolutional neural network

4 Simulation Results

In this section, the performance of the proposed OMCM-CNN algorithm is evaluated. In order to explore the practical application significance of our proposed algorithm, we consider the OFDMA sensing problem under 5G NR system parameters. We consider an OFDMA system with $K = 16$ PUs and 4 096 subcarriers, where 3 072 subcarriers are used for communication and 512 subcarriers on each band side are considered as the guard interval. The bandwidth of a single subcarrier is set to W_{sub} = 30 kHz and the total bandwidth of the system is W_B = 30 kHz × 4 096 = 122.88 MHz. At each sensing time, an SU with $M = 8$ antennas can sample the received signal to get $N_{sym} = 100$ OFDM symbol $\boldsymbol{Y}$ for spectrum sensing. According to the Third Generation Partnership Project (3GPP) 38.211 standard, each resource block (RB) contains $N_f = 12$ subcarriers and a single subchannel contains $N_r = 4$ RB. Thus, the total number of subchannels can be calculated by $B = 3\,072/(N_r \times N_f) = 64$. PU k occupies B_k consecutive subchannels with probability $P_k = 50\%$ at each sensing time where B_k is randomly selected from the integer set $\{2, 3, 4, 5, 6\}$ and randomly chooses BPSK, QPSK or 4QAM as its modulation mode. The average SNR is set to $c = -10$ dB and the SNR fluctuation factor is set to $w = 2$ dB. As for the channel model, the channel gain power $\sigma_h^2(l)$ at impulse l is set according to Tapped Delay Line (TDL)-B model in 3GPP 38.901 standard, where the normalized time delay is set to 100 us. Furthermore, we assume that the length of CP is 1 000, $\rho = 0.75$ and $D = 0.5$ dB. In the preprocessing stage, we concatenate the subcarrier covariance matrices with $B = 64$ into the OFDM multicarrier covariance matrix array where $P = 8$ and $Q = 8$. The specific hyperparameters of the proposed covariance matrix-aware CNN are given in Table 2.

▼Table 2. Hyper parameters of the proposed CNN

Input: Multicarrier Covariance Matrix Array (64 × 64 × 2)	
Layers	Convolution Kernel Size
C1+ ReLu	128@(3 × 3), padding, stride = 1
M1	2 × 2, stride = 2
C2+ ReLu	128@(3 × 3), padding, stride = 1
M2	2 × 2, stride = 2
C3+ ReLu	256@(3 × 3), padding, stride = 1
C4+ ReLu	256@(3 × 3), padding, stride = 1
M3	2 × 2, stride = 2
F+ Sigmoid	16 384 × 64
Output: Feature Vector (64 × 1)	

CNN: convolutional neural network ReLu: rectifier linear unit

We take the ED[5], MME[8], AGM[9], MSEE[10], ME-AM, and ME-GM[11–12] as the benchmark to evaluate our proposed method. Note that these baseline algorithms are introduced for narrowband spectrum sensing and applied to the OFDMA system in each subband separately. The PD and PFA in the simulation results are defined as the averaged value of all subchannels by 10 000 Monte Carlo realizations.

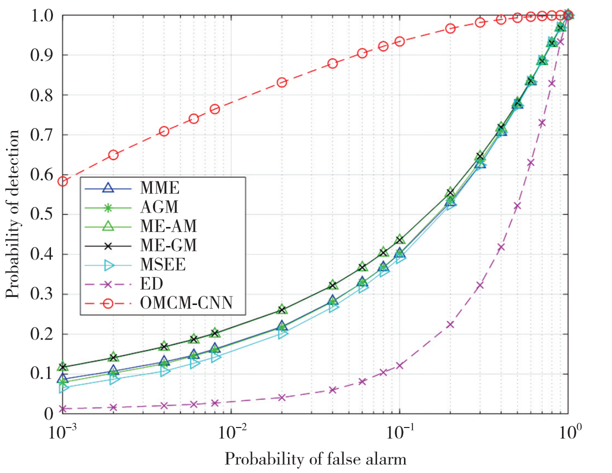
Fig. 4 depicts the receiver operating characteristic (ROC) curves of respective algorithms, i.e., PD versus PFA. It can be observed from Fig. 4 that the ED which relies on only the energy information has the lowest performance essentially due to the presence of NU. Eigenvalue-based methods (MME, AGM, MSEE, ME-AM, and ME-GM) also achieve an unsatisfactory performance since these methods ignore the energy information and the correlation information between subchannels. The performance of the proposed OMCM-CNN method is significantly better than those of other baseline methods since it comprehensively combines the energy information of the received signal and the correlation information between the antennas and subchannels. Fig. 5 depicts the ROC curves with the number of antennas $M = 64$ and the other parameter setting is kept the same as Fig. 4. We see that the proposed method still exhibits the best performance, and with the increase in the number of antennas, the spectrum sensing performance of all algorithms is further improved.

Next, we explore the influence of different OFDM symbol sampling numbers N_{sym}, i.e., PD versus N_{sym}. We set $M = 8$, $w = 2$ dB, and $c = -10$ dB, and PFA is set to 0.1 according to IEEE 802.22 standard. Fig. 6 shows the PD of each algorithm under different sampling numbers with N_{sym} from 20 to 200. In practice, we can achieve a high N_{sym} by extending the sampling time or setting multiple sensors to sample. It can be seen from Fig. 6 that the performance of the proposed algorithm is better than other traditional algorithms under all N_{sym}. As expected, the performance of the proposed algorithm and the eigenvalue-based methods improves as the sampling number N_{sym} increases. This is because in the case of large N_{sym}, the statistical characteristics of the received signal have a more accurate estimate at a higher sampling number. However, the ED has a poor performance and has no improvement under different sampling numbers. This phenomenon is incurred by NU and SNR fluctuation, which causes huge interference to the energy information. That is to say, even with a large number of sampling numbers, the statistical characteristic of the energy information still cannot be correctly estimated.

Finally, we plot the PD versus different averaged SNR c in Fig. 7 to test the robustness of the proposed algorithm. We set $M = 8$, $N_{sym} = 100$, and PFA is set to 0.1 according to IEEE 802.22 standard. It can be observed from Fig. 7 that the proposed CNN method achieves the best performance under different SNRs. The performance of all algorithms improves significantly as the SNR increases. The ED still achieves an unsatisfactory sensing performance with SNR increasing since it is greatly disturbed by the NU, which shows that it is not feasible to perform multicarrier sensing based on only the energy information.

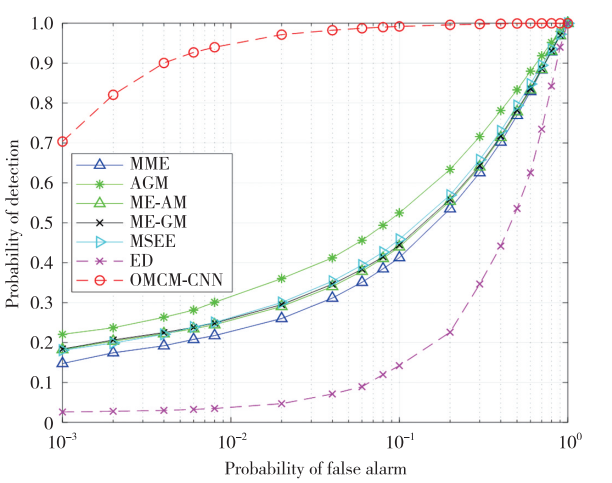
5 Conclusions

In this paper, we have investigated the spectrum sensing problem in the OFDMA scenario under the 5G NR network and developed a spectrum sensing method based on the multicarrier covariance matrix aware-CNN. The proposed approach can effectively learn the energy and the correlation informa-



AGM: arithmetic to geometric mean ED: energy detection
ME-AM: maximum eigenvalue-to-arithmetic mean
ME-GM: maximum eigenvalue-to-geometric mean
OMCM-CNN: OFDM multicarrier covariance matrix-convolutional neural network
MME: maximum-minimum eigenvalue
MSEE: mean-to-square extreme eigenvalue

▲ **Figure 4. Receiver operating characteristic (ROC) curves of different algorithms with M = 8**



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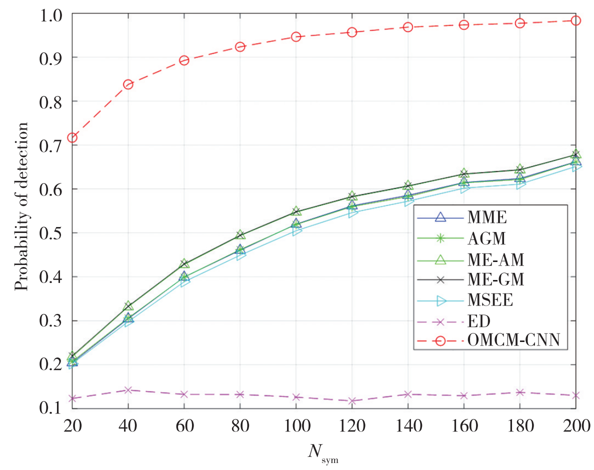
▲ **Figure 5. Receiver operating characteristic (ROC) curves of different algorithms with M = 64**

tion between antennas and between subcarriers to further improve the sensing performance. Simulation results in the OFDMA scenarios under 5G NR network have illustrated the superior performance of the proposed method over several state-of-the-art algorithms.



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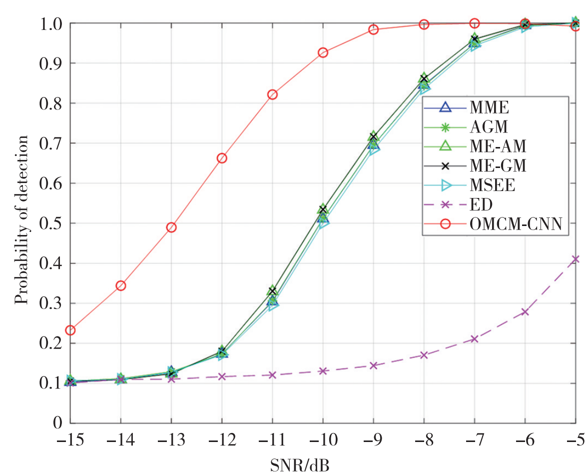
▲ **Figure 6. Probability of detection with different number of samples N_{sym} with probability of false alarm (PFA) = 0.1**



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SNR: signal-to-noise ratio

▲ **Figure 7. Probability of detection with different average SNR c under probability of false alarm (PFA) = 0.1**

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