Received November 20, 2019, accepted November 26, 2019, date of publication December 2, 2019, date of current version December 17, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2956958

Opportunistic Spectrum Access for UAV Communications Towards Ultra Dense Networks

SHAN LUO[1,2], YONG XIAO[3], (Senior Member, IEEE), RONGPING LIN[4], XIANGDONG XIE[5], GUOAN BI[6], (Senior Member, IEEE), YUWEI ZHAO[7], AND JIYAN HUANG[8]

[1]School of Aeronautics and Astronautics, University of Electronic Science and Technology of China (UESTC), Chengdu 611731, China
[2]Aircraft Swarm Intelligent Sensing and Cooperative Control Key Laboratory of Sichuan Province, UESTC, Chengdu 611731, China
[3]School of Electronic Information and Communications, Huazhong University of Science and Technology, Wuhan 430074, China
[4]School of Information and Communication Engineering, UESTC, Chengdu 611731, China
[5]School of Aeronautics and Astronautics, UESTC, Chengdu 611731, China
[6]School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798
[7]School of Aeronautics and Astronautics, UESTC, Chengdu 611731, China
[8]School of Information and Communication Engineering, UESTC, Chengdu 611731, China

Corresponding author: Rongping Lin (linrp@uestc.edu.cn)

This work was supported in part by the National Natural Science Foundation of China (NSFC) under Grant 61701079 and Grant 61871097, and in part by the Key Research and Development Project of Sichuan Science and Technology Department under Grant 2019YFG0086.

ABSTRACT The growing popularity of unmanned aerial vehicle (UAV) attracts significant research interests and applications including low-altitude and airborne vehicles. Since there is no declared spectrum allocated to UAV communications, opportunistic transmission has been commonly considered as an important way for supporting UAV communications. When sharing the same spectrum with other users such as satellites and mobile base stations, accurate spectrum sensing and allocation are of critical importance for UAV communications to avoid serious interference. As the UAVs can constantly move to different locations with various spectrum environments, the spectrum decision may be invalid only in a short period, leading to require fast spectrum sensing. Furthermore, an UAV needs to predict possible temporal and spatial vacations of the spectrum. In this case, the spectrum prediction has a high dimensional state space which is notoriously difficult to solve. In this paper, some other issues such as how to determine the spectrum processing time and how to detect the primary signals with high priority to avoid interference, are also discussed. Finally, a fast spectrum sensing algorithm is proposed to improve the energy detection performance by optimizing the error estimation and a constant ratio of missed detection. Our proposed algorithm does not require high computational capability and can achieve relatively accurate sensing in low signal-to-noise ratio scenarios.

INDEX TERMS Unmanned aerial vehicles, ultra dense networks, spectrum management, spectrum sensing.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have been widely applied to applications such as aerial photogrammetry, plant protection, security, live broadcast and video screaming. They can be low-altitude platforms (LAPs) of altitude 0∼1 km and airborne vehicles of altitude 1∼20 km [1]. Currently, UAV systems coexist with other systems such as mobile, airborne, and satellite communications in the same spectrum bands. Recently, the FCC adopted new rules for the millimeter wave (mmWave) spectrum above 28GHz, i.e., 27.5∼28.35GHz, 37∼38.6GHz, and 38.6∼40GHz, requesting further comments on sharing these bands between satellite, terrestrial 5G and other unlicensed users. These bands include the spectrum currently occupied by some high-altitude UAV communications as in the Ku∼Ka bands. Another example is that some LAPs like multi-rotor UAVs/drones operated in 840MHz∼2.4GHz band which overlaps with ground cellular base stations and satellite communication/navigation for civilian airplanes. To avoid interference between different technologies, the spectrum access and scheduling between different systems must

The associate editor coordinating the review of this manuscript and approving it for publication was Fuhui Zhou.

be carefully managed. Opportunistic spectrum access is a promising solution to alleviate cross-interference among coexisting technologies. Each UAV needs to first sense the spectrum [2] and only access the spectrum that is vacant at the moment.

Since the UAV moves from one locations to another, the sensing/detection result of spectrum occupancy is only valid within a short period. This has been exacerbated by the fact that the ultra dense networks (UDNs) consisting of a large number of closely located base stations (BSs), i.e., 50$\sim$1000 BSs/km^2 [3], [4] or with distances about 30$\sim$150 m, will be quite popular in 5G systems. In this case, UAVs are expected to switch among different cellular BSs more frequently causing uncontrollable and uncertain dynamics for UAVs' spectrum environments. For example, a drone with velocity 20 m/s and altitude 500 m can transfer from one BS to another with a distance of 50 meters within 2.5 seconds, indicating that the user may transfer into another wireless environment in such a short period. In this period, the users should implement spectrum sensing, accessing and communication, where the last procedure consumes the most time. Therefore, the time of spectrum sensing should be much less for UAVs comparing to the terrestrial users with no and low speeds, requiring that the spectrum sensing must be fast and be able to adopt to such highly time varying environments.

One way to improve the spectrum sensing is to perform spectrum prediction [5]. Different from the terrestrial communications where the users generally predict spectrum based on the historical information only in the temporal dimension, the UAVs should predict based on the historical information according to both temporal and spatial variations, since the UAVs are constantly changing wireless environments. Currently, how to predict the spectrum dynamics by jointly considering the information of temporal and spatial dimensions is still a challenging problem for UAV systems.

In this article, we first describe the opportunistic transmission for UAVs and discuss some challenges. Then we propose a fast and accurate algorithm of spectrum sensing in a fast-changing environment. The main contributions include two improvements. One is optimizing the noise power estimation to improve the energy detection (ED) based spectrum sensing. As a simple and fast sensing approach, the ED has been widely adopted in many applications where the sensing time is limited [2], [6]. Unfortunately, the ED usually suffers from the errors of estimated noise power, or commonly referring to as the noise uncertainty [7]. This problem is so crucial that it makes the ED-based sensing become inefficient when the signal-to-noise ratio (SNR) is much decreased. An important reason why the noise parameters cannot be accurately estimated is that the statistics of noise in different frequency bands are not accurately evaluated since a strict i.i.d. property is generally not satisfied in practice. We will present a new perspective to solve this problem that the convex optimization [8] is introduced to improve the estimated noise power. It is reported that the convex optimization has been used to overcome the problem caused by dependent statistics, such as the dependent sources separation [9]. The reason is that the performance of convex optimization is mainly related to whether the design of optimization model is reasonable or not. In another word, the focus of the problem is transferred from the statistical property to the optimization model. Therefore we propose a new scheme for ED by optimizing parameters of noise estimation, referring to as the optimized noise estimation based ED (ONED). Simulations indicate that the noise variance estimation becomes much more accurate after optimization by low computational costs. As the final detection performance is experimentally improved comparing to the conventional ED, the proposed ONED could be considered as an efficient approach for fast spectrum sensing.

Another contribution is introducing a decision rule based on the constant missed detection rate (CMDR). Conventional signal detection usually employs the constant false alarm rate (CFAR) based decision rule, where the false alarm rate is pre-fixed and the detection probability is varying at different SNRs. However, for UAV second users, the missed detection rate is more crucial than the false alarm rate because the second users would have interference to the primary users if the missed detection rate is high. Therefore the missed detection rate should be fixed to ensure the primary signal can be always effectively detected at different SNRs. We will propose a CMDR based ED, giving a theoretical threshold determined by a pre-set missed detection rate. Finally, the CMDR is jointly used with the ONED to sense the primary signals.

The rest of this paper is organized as follows: In Section II we review the existing works and describes the scheme of opportunistic spectrum access for UAV communications. Main challenges and potential research topics are discussed in Section III. Finally, we propose a spectrum sensing algorithm in Section IV-A. This algorithm employs the linear programming (LP) method to optimize the noise estimation to improve the energy detection (ED), leading to a fast and accurate sensing approach which can work at SNR $= -13$ dB with low complexity. A modified decision rule in sense of CMDR is also considered for the sensing algorithm. Finally, we conclude this article in Section V.

II. OPPORTUNISTIC TRANSMISSION FOR UAVs

UAVs have attracted significant interests recently. Both low altitude and airborne UAVs are widely adopted in applications such as environmental monitoring, smart agriculture, etc. However, according to the altitudes and speeds of UAV systems, the spectrum sensing and accessing requirements are generally different. In particular, at low altitude 0$\sim$1 km, UAVs including drones and fixed-wing planes mainly communicate in low frequency bands noted as the sub-6GHz. Some of them can also operate in licensed bands such as 840MHz, 1.4GHz and 2.4GHz for applications of aerial photogrammetry, plant protection and military. Most LAP-UAVs may employ opportunistic transmission to access unlicensed spectrum. At the altitude 1$\sim$20 km, UAVs, which are mainly fixed-wing planes, may transmit in higher frequency bands

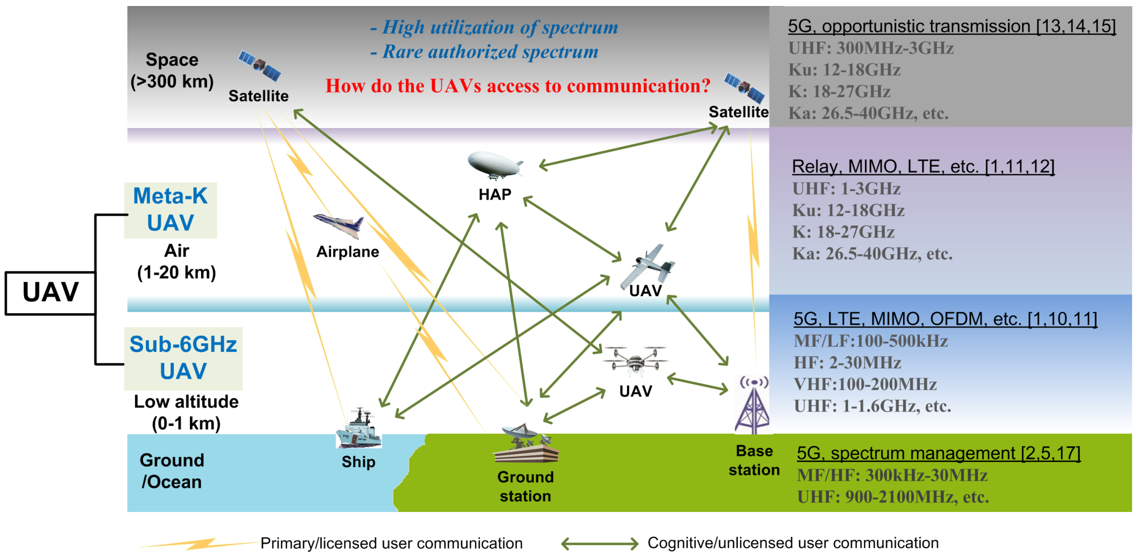


FIGURE 1. The wireless communications of UAVs by using opportunistic spectrum access.

such as Ku, K and Ka bands (12∼40GHz), with possible extension to other mmWave bands (30∼300GHz). Therefore we can classify the UAVs into two categories of **sub-6GHz UAVs** and **meta-K UAVs**, similar to the suggestion of FCC for 5G communications. It is worth to note that the LAP-UAVs may also use the Ka-band as the FCC has decided to release some mmWave bands for better communication services.

For different categories, the communication mechanism should be designed specifically for issues including data rate, capacity, bandwidth, antenna and so on. For instance, the meta-K UAVs are able to transmit at high data rates while the sub-6GHz UAVs communicate at lower rates. In following content, we will discuss several issues of the difference between the two categories.

Next we briefly review some communications related to the UAVs, including communications based on satellites, high-altitude platforms (HAPs), airplanes, LAPs, and so on. Then we will describe the procedure of spectrum sensing and prediction.

A. COMMUNICATIONS RELATED TO UAVs

There are many wireless transmissions in or through the air, related to the UAV communications, as shown in Figure 1. Some topics are briefly concluded as follows.

1) LAP/AIRBORNE COMMUNICATIONS

The LAP/airborne UAVs have been developed for decades and widely used in many scenarios, including drones flying at low altitudes and fixed-wing planes flying at higher altitudes. The literatures show that the LAP communications are closely related to the terrestrial communications [10]. Since both of their altitudes and speeds are not very high, the terrestrial communication theories and architectures are adopted in LAP communications, including 5G, LTE and MIMO based technologies [1], [11].

2) HAP COMMUNICATIONS

In recent years, the HAPs working in the near space (altitude 20∼100 km) have attracted much interests, especially for applications of relay platforms and navigation. Many schemes have been proposed to design the communication frameworks, including wideband, MIMO, LTE and OFDM based communications [11], [12]. The HAP communications work in the Ku∼Ka bands as the same as the satellite communications.

3) SUPERSONIC/HYPERSONIC AIRCRAFT COMMUNICATIONS

At present, the supersonic/hypersonic aircrafts in the near space are mainly employed for military purposes such as for SAR imaging. For civilian using, some plans have been proposed to send special people to destinations in very short time, such as the "AS2" which is now being developed by Airbus & Aerion with a speed of Mach 1.6, and the model of "Antipode" jet which is designed to fly at a speed of Mach 24 with 10 passengers. However, the communications for supersonic/hypersonic aircrafts are not maturely investigated. In another word, there are many topics in this area, e.g., communication interruption caused by large doppler shift and blackout problem of plasma sheath.

4) SATELLITE COMMUNICATIONS

The demands of satellite communications are highly increasing, e.g., "Digital Agenda for Europe" was defined to require broadband speeds of at least 30 Mbps to all users in Europe and 100 Mbps to at least 50% of households by 2020, where the number of users is expected to grow up to

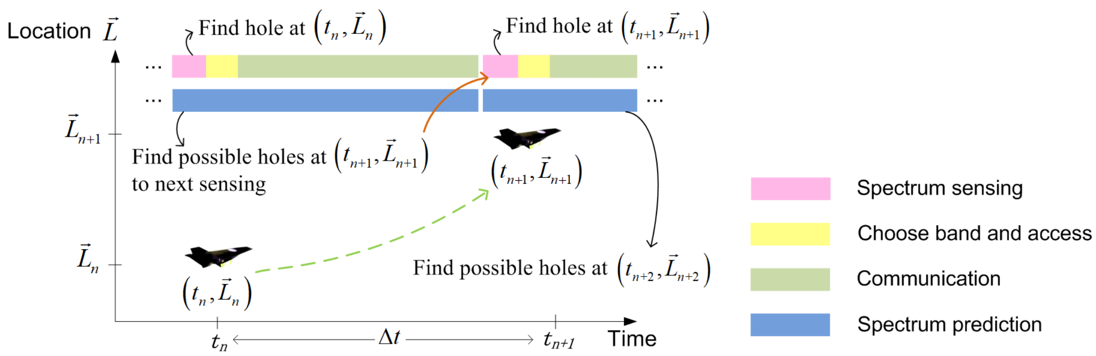


FIGURE 2. Spectrum prediction and sensing for UAV communications.

5∼10 Million [13]. Cognitive spectrum utilization is an efficient solution to meet such ambitious requirements of satellite communications by sharing spectrum with other users to increase both of bandwidth and data rates [14], [15]. As an important step in spectrum awareness, spectrum sensing is developed to detect signals at a SNR as low as −10 dB [13].

5) TERRESTRIAL COMMUNICATIONS

A typical example of terrestrial communications related to the UAV transmissions is the mobile communication. For spectrum sensing, many reports have introduced various methods including ED, cyclostationary, eigenvalue, compressed sensing based methods and so on [2]. Moreover, to further improve the efficiency of spectrum sensing, spectrum prediction has been proposed to predict possible holes before sensing [16]. In literature, many prediction approaches have been introduced such as neural network model, autoregressive model, machine learning, and Markov model/hidden Markov model based methods [17]. The joint use of prediction and sensing greatly reduces the sensing time comparing with sensing all or random bands. At the same time, it also improves the sensing accuracy as the predicted holes are probable idle.

B. OPPORTUNISTIC SPECTRUM ACCESS

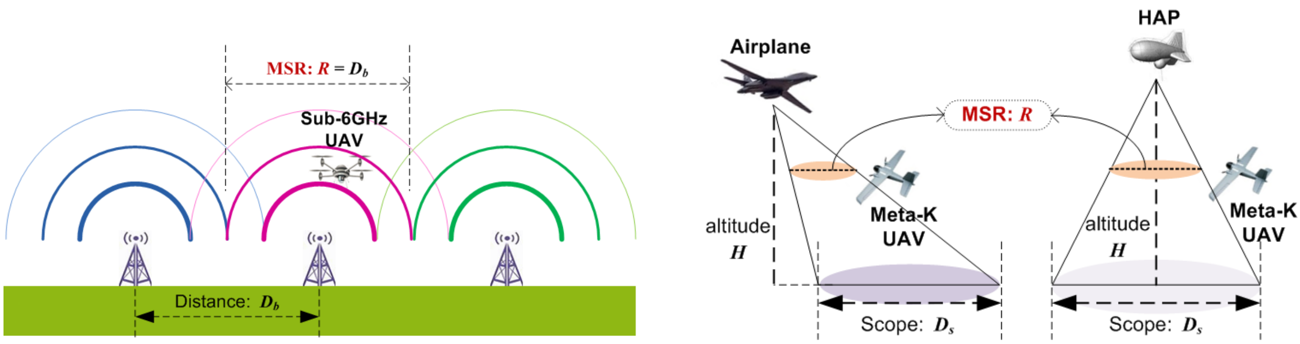
From Figure 1 it is observed that the UAV communications work in the air, sharing the same areas with other transmissions. Therefore, it is expected that the UAVs would perform communication in the way of opportunistic transmission, e.g., access a spectrum hole or share spectrum with other users. The UAV communications are not allowed to interfere the licensed communications, including ground ↔ satellite, ground ↔ civilian airplane, satellite ↔ airplane, etc., as shown in Figure 1. Some of these licensed communications, e.g., civilian airplane related communications, have very high priority in using the spectrum, i.e., no interference should be allowed since an interference may cause serious accidents. This leads to that the detection of sensing the primary signals must be as accurate as possible, or the missed probability should be low enough. Therefore, it is required a spectrum sensing approach achieves a very low missed detection rate, while the false alarm probability seems to be not crucial.

A more important issue of the spectrum sensing is the limited time cost as the UAVs travel different wireless environments in a short time period. It is known that the time cost is mainly determined by the complexity of method, while there is a trade-off between the complexity and the sensing accuracy. That is, the requirements of fast and accurate sensing are difficult to be meet at the same time. Therefore the spectrum prediction is implemented to reduce the complexity of sensing procedure, as well as to improve the sensing accuracy. In this way, it is only to sense the predicted possible holes instead of all or random frequency bands [16]. However, the prediction methods for terrestrial communications could not be directly deployed on the UAV communications, since the terrestrial users with low speeds would not frequently change wireless environments. For terrestrial users, the spectrum prediction needs the historical information of the temporal dimension only. For UAVs, the prediction needs the historical information of both time and space.

The spectrum access procedure of the UAV communications can be simply illustrated in Figure 2. In this figure, $(t_n, \vec{L}_n)$ denotes the temporal-spatial index of the nth wireless environment, where $\vec{L}_n$ is a 3D location including latitude, longitude and altitude. The interval Δt between the nth and $(n+1)$th time instants is the travel duration from one wireless environment to the next. In Δt, two procedures are parallel implemented as one is ''spectrum sensing → access → communication'', and another is ''spectrum prediction''. Especially, the prediction occurred at $(t_n, \vec{L}_n)$ is actually finding possible holes at $(t_{n+1}, \vec{L}_{n+1})$. From Figure 2 it is observed that the time required by sensing/prediction is closely related to Δt, implying that Δt is a crucial parameter.

III. OPEN ISSUES

Although the opportunistic transmission has been employed on scenarios such as the mobile and satellite communications, there are still some challenges when it is used for UAV communications. We briefly conclude four possible issues in this section, as follows.



(a) a sub-6GHz UAV flying in wireless coverage of base stations

(b) a meta-K UAV traveling in wireless coverage of airplane/HAPs

FIGURE 3. Two examples for the definition of MSR: *R*.

A. MINIMUM SPECTRUM RANGE

It has been noticed that the interval of traveling between two environments, Δt in Figure 2, is an important factor that decides the time duration required by sensing and prediction. Let us first consider how to how to define Δt. Since the traveling time duration equals to $\frac{distance}{speed}$, if the distance could be confirmed, the traveling time is easily calculated by a specific speed. Therefore we transfer this problem with two factors of distance and speed into a new one with only one factor of distance, as the speed of UAV can be obtained easily. We define the minimum range of one wireless environment to be the distance related to Δt, denoted as **minimum spectrum range** (MSR) to indicate the minimum valid scope of one sensing result. When the UAV travels to exceed the MSR, the wireless environment is believed changed and the UAV must interrupt communication and re-sense the spectrum.

We may explain how to define the MSR by two examples. One is for the sub-6GHz UAVs such as a drone, shown in Figure 3(a). It can be observed that the MSR actually is the range of base station, i.e., the MSR $R = D_b$ where D_b denotes the distance between adjacent base stations. In fact, the UDN based BSs are built closely as D_b is in the range of 30$\sim$150 m, resulting that Δt is in the range of 1.5$\sim$7.5 seconds when the drone flies at a velocity of 20 m/s. Another example is for the meta-K UAVs shown in Figure 3(b). In the air, the MSR is mainly determined by the airplane and HAP communications since other users such as satellites usually cover relatively larger scopes. By the ground scope of airplane/HAP communication (denoted as D_s) and the altitudes of airplane/HAP & meta-K UAV (denoted as H & H_{UAV}), the MSR can be calculated as $R = (H - H_{UAV})D_s/H$. For instance, an airborne P3/SAR works with $H = 7620$ m, $D_s = 3.2$ km, $v = 608$ km/h, plus a UAV for topography flies at $H_{UAV} = 5000$ m with $v_{UAV} = 70$ km/h in the opposite direction, then the MSR would be 1.1 km and $\Delta t = \text{MSR}/(v + v_{UAV}) \approx$ 5.84 seconds. It is hoped these two simple examples may give some ideas on the discussion of MSR.

B. FAST ALGORITHMS FOR SPECTRUM PREDICTION AND SENSING

The UAVs may transfer into new environments in several seconds, implying that the spectrum prediction and sensing must be accomplished in such a short time duration. Specifically, from Figure 2 it is observed that the time duration required for spectrum prediction could be simply as Δt, while that for sensing is much less than Δt since the communication would make use most of Δt. For example, the sensing time may be set in the order of millisecond (ms) if Δt equals to a couple of seconds. It may be different from the situation of the terrestrial communications where the processing time is more than a couple of seconds. This issue may be not easily deal with because the algorithms are also required to be highly accurate at low SNRs, e.g., SNR may be -6.5 dB for 500 meters above the BS [18]. Although some reports show that the sensing time is as small as in the order of microsecond (μs), the SNR is required > -5 dB [19] that could not be employed here. In Subsection IV-A we will introduce a fast approach for spectrum sensing, working at SNR $= -13$ dB. This approach may be used for UAV communications since it requires time duration in the order of ms in simulations.

C. SPECTRUM PREDICTION BASED ON TEMPORAL-SPATIAL INFORMATION

The UAV communications need to predict possible holes in the next time and next space location. Comparing to the terrestrial prediction which gives possible holes in the next time but at the same location, the theory and algorithms for UAV prediction become much more complex as this problem seems to be of high dimensions.

For unlicensed sub-6GHz UAVs, there is another situation that although a suitable hole is found, a licensed user begins to access the hole just after the UAV starts to communicate. This is because the sub-6GHz bands are maturely developed, containing a large number of users with high spectrum utilization. To avoid the conflict, it should be predicted to be the spectrum idle time (or spectrum occupancy) [20]. Among the possible holes predicted firstly, some holes with enough idle time for the UAV communication are selected for the next spectrum sensing. That is, the predicted holes should be possibly with an idle period approximating to Δt. Of course, the prediction of spectrum idle time is also based on the temporal-spatial information.

Besides, how to generate the data base of temporal-spatial information is another important topic. If the data base saves information of each point in dimensions of time, latitude, longitude and altitude (similar to the terrestrial data base with information of each time slot), it would be a difficult and huge work. This problem may be approximated to some simple boundary issues such as homotopy based models, to reduce the prediction complexity.

D. CONSTANT MISSED DETECTION RATE BASED SPECTRUM SENSING

In literature, many works reported that the spectrum sensing is based on the detection theory of CFAR, which is detecting signals by a threshold decided from a pre-defined false alarm probability. The CFAR based detection is widely used in many fields such as radar where the false alarm probability should be fixed. However, for some UAV communications, the missed rate may be more crucial. In this situation, the false alarm probability is not cared since the cost of sensing another hole may be much less than the cost of interfering licensed users with a missed detection. Therefore a new topic of constant missed rate based spectrum sensing may give a solution, implying that the threshold is determined by a pre-defined missed rate or detection probability. This issue will be further discussed in Subsection IV-B.

IV. AN IMPROVED ENERGY DETECTION FOR FAST SPECTRUM SENSING

In this section, we will show a fast sensing scheme based on the ED for UAV communications. There are two contributions for improving the ED including an optimization of noise estimation errors, and a modified decision rule to maintain the missed detection rates.

A. AN OPTIMIZED NOISE ESTIMATION BASED ENERGY DETECTION

The ED usually suffers from the errors of estimated noise. That is, the estimated noise variance $\tilde{\sigma}_e^2$ generally has some errors comparing with the true value σ^2, leading to an inappropriate threshold which does not differentiate the signal and noise. As a result, the accuracy of detection is seriously degraded including low detection probability or high false alarm probability. One reason for poor performance of noise parameter estimation is that the statistics of noise in different frequency bands are not accurately evaluated. It is known that the problem caused by inaccurate statistical model is usually difficult to be solved in conventional estimation methods. Therefore, it is necessary to seek some solution that is not relied on the statistic property.

Generally, for engineering, the convex optimization considered in signal detection is theoretically nonsensitive to the statistics of decision variables [8]. The reason is that the performance of convex optimization is mainly related to whether the design of optimization model is reasonable or not. In another word, the focus of the problem is transferred from the statistical property to the design of optimization model. Therefore it can be employed to solve problems caused by poor statistic property.

Motivated by the idea of using convex optimization to improve practical performance, we introduce a new scheme for ED by optimizing parameters of noise estimation, referring to as the ONED. The optimization problem for estimated noise is formulated by linear programming (LP) method, which is a special case in the convex theory [8]. Simulations indicate that the noise variance estimation becomes much more accurate after optimization by low computational costs. As the final detection performance is experimentally improved comparing to the conventional ED, the proposed ONED could be considered as an efficient approach for fast spectrum sensing.

1) BASIC ASSUMPTIONS OF THE ED

Let us briefly review the procedure of ED. At the receiver, we have a typical binary hypothesis testing expressed as

$$\begin{aligned} &H_0 : x(t) = w(t), \quad (\textit{spectrum hole}) \\ &H_1 : x(t) = s(t) + w(t), \quad (\textit{no spectrum hole}) \end{aligned} \tag{1}$$

where $x(t)$, $s(t)$ and $w(t)$ denote the received signal, clean signal and noise, respectively. Here we consider $w(t) \sim N(0, \sigma^2)$, where σ^2 is the noise variance needed to be estimated. If the estimated noise variance is accurate, we can perform the conventional ED as [21]

$$\gamma = \frac{1}{T}\int_T |x(t)|^2 dt \Rightarrow \begin{cases} > V_T \rightarrow H_1, \\ \leq V_T \rightarrow H_0, \end{cases} \tag{2}$$

where V_T denotes the detection threshold. If the CFAR based decision rule is adopted, the threshold V_T can be calculated by a pre-defined false alarm probability P_{fa}.

2) THE LP-BASED OPTIMIZATION OF ESTIMATED NOISE

The ED is very vulnerable to the estimation errors of noise, i.e., the estimation error e_e ($e_e = |\sigma - \tilde{\sigma}_e|/\sigma$) much degrades the detection performance. In another word, if the noise estimation is improved to give a more accurate result, the accuracy of detection can be further improved. Figure 4 describes a spectrum model including signals, noise and spectrum holes. Among them, there are some special reversed bands which are not generally opened, implying that they are probably idle. Usually, the noise levels in different bands are not the same, even if these bands are all idle such as spectrum holes or reserved bands. If the noise power is estimated with errors, we propose an optimization scheme to solve this problem. The optimization for estimated noise standard variance $\tilde{\sigma}_e$ can be modeled as the following

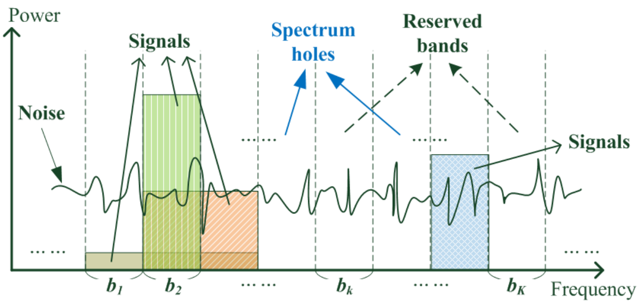


FIGURE 4. **A spectrum model including signals, noise, reserved bands and spectrum holes in K bands.**

problem,

$$\begin{aligned} & min\ \Delta\sigma, \\ & s.t.\ \Delta\sigma \geq \left|\sigma_k - \tilde{\sigma}_{e_k}\right|, \quad \sigma_k > 0,\ for\ all\ k, \\ & \quad \sum\nolimits_{k=1}^{K} \sigma_k = K\bar{\sigma} + \epsilon, \end{aligned} \tag{3}$$

where σ_k and $\tilde{\sigma}_{e_k}$ are the standard variances of true and estimated values for noise in different frequency bands b_k, $k = 1 \sim K$, respectively; $\Delta\sigma$ denotes the absolute difference between the true and estimated values; $\bar{\sigma}$ is called an average noise level, pre-provided by special idle bands such as some reserved bands; ϵ is a pre-set parameter to control the precision of standard variances. The model in (3) is to minimize the difference between true and estimated values for all bands, providing a solution of optimized estimation of noise, denoted as $\tilde{\sigma}_{opt_k}$ for all k bands. As the unlicensed users implement spectrum prediction before spectrum sensing [16], the number of bands, K, to be sensed is not large since the spectrum prediction usually provides a limited number of possible holes. Therefore our optimization is a small scale problem and we employ the algorithm of Simplex to solve the model in (3), as shown in Algorithm 1. In the problem in (3) , the true standard variances σ_k are the variables which are attempted to be solved, formed as the vector $\mathbf{X}$ in the Algorithm 1. The constraints in (3) are transformed to a relationship of $\mathbf{A}\cdot\mathbf{X}=\mathbf{b}$ including the coefficient matrix $\mathbf{A}$ and vector $\mathbf{b}$ of estimations. With the matrix of $\mathbf{A}$, we transfer the absolute value inequalities into a bunch of linear inequalities. Then the problem can be input into the LP tool CPLEX and calculated the optimal solution easily by the following steps:

a) Use the coefficient matrix $\mathbf{A}$ to transfer the absolute value constraints into linear ones.

b) Set the value of the matrix production according to standard variance estimations $\tilde{\sigma}_{e_k}$.

c) Use CPLEX to find out the optimal solution $\Delta\sigma$ and get the optimal noise estimations $\tilde{\sigma}_{opt_k}$. Make sure the second constrain in problem (3) is satisfied at the same time.

Before the optimization, there are two parameters $\bar{\sigma}$ and ϵ needed to be set. In simulations, $\bar{\sigma}$ is set as the average noise standard variance of several reserved idle bands. It should be noted that these idle bands are not included in K sensing bands. Moreover, the true noise levels in idle bands and K sensing bands are not the same, i.e.,

$$\sigma_i \neq \sigma_j \neq \sigma_l \neq \sigma_k, \quad \text{for} \ \ i \neq j \ \ \text{and} \ \ \ l \neq k,$$

where σ_i & σ_j are from J idle bands with $(i, j = 1, 2, \ldots, J)$, and σ_l & σ_k are from K sensing bands with $(l, k = 1, 2, \ldots, K)$ including busy bands and spectrum holes. However, we believe that the average true value of K sensing bands is equal to $\bar{\sigma}$ since the noise from different bands in a certain environment has the same background. The setting of ϵ is based on experimental results. Numerical tests show that $\epsilon = 0.001$ is a good choice that the optimized errors e_{opt} are the smallest, where

$$e_{opt} = |\sigma - \tilde{\sigma}_{opt}|/\sigma \tag{4}$$

presenting the errors between the true and optimized values.

Table 1 presents the average optimized errors e_{opt} by 1000 Monte Carlo trials with estimated errors $e_e = 0.05, 0.10$ and 0.15, SNR $= -18, -16, -14$ and -12 dB, the number of sensing bands $K = 2$, 4, and 8. It is observed that the optimized errors of noise standard variances are mostly in the order of 10^{-3}, which are much smaller than the estimated errors e_e, indicating that the optimization procedure designed

---

Algorithm 1 The LP-Based Optimization for Noise Variance Estimation

Input: standard variance estimation $\tilde{\sigma}_{e_k}$, average noise level $\bar{\sigma}$, ϵ.
Output: optimized estimations of standard variances, denoted as $\tilde{\sigma}_{opt_k}$.
BEGIN:

1 According to the constraints in (3), it can be set that the restriction $\Delta\sigma \geq \left|\sigma_k - \tilde{\sigma}_{e_k}\right|$ is ensured by $\mathbf{A}\cdot\mathbf{X}=\mathbf{b}$, with the coefficient matrix as $\mathbf{A} = \begin{bmatrix} M_{-1} & diag_1^K \\ M_1 & diag_1^K \end{bmatrix}$, where

$$M_1 = [\underbrace{1, 1, \ldots, 1}_{K}]^T, \quad M_{-1} = [\underbrace{-1, -1, \ldots, -1}_{K}]^T,$$

$$diag_1^K = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \ddots & 0 & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \cdots & 0 & 1 \end{bmatrix}.$$

2 Set $\mathbf{b} = \left[\tilde{\sigma}_{e_1}, \tilde{\sigma}_{e_2}, \ldots, \tilde{\sigma}_{e_K}, -\tilde{\sigma}_{e_1}, -\tilde{\sigma}_{e_2}, \ldots, -\tilde{\sigma}_{e_K}\right]$, and $\mathbf{X} = [\sigma_1, \sigma_2, \ldots, \sigma_K]$.

3 Calculate $\mathbf{X}$ satisfied $\mathbf{A}\cdot\mathbf{X}=\mathbf{b}$ by LP tools. For example, input $\mathbf{A}$, $\mathbf{b}$ and $\mathbf{X}$ into the CPLEX.

4 Make sure $\mathbf{X}$ satisfied $\sum_{k=1}^{K} \sigma_k = K\bar{\sigma} + \epsilon$ at the same time.

5 Calculate the value of $\Delta\sigma$ and check its optimality. Do steps 3 $\sim$ 5 iteratively in CPLEX until the minimum $\Delta\sigma$ is obtained.

6 Return $\mathbf{X}$.

END

TABLE 1. Average optimized errors e_{opt} ($\times 10^{-3}$, $\epsilon = 0.001$).

$K = 2$:	SNR (dB)	$e_e = 0.05$	$e_e = 0.10$	$e_e = 0.15$
	-18	0.7790	1.5919	2.3289
	-16	0.7847	1.5934	2.3562
	-14	0.7866	1.6059	2.4582
	-12	0.7982	1.6197	2.4683
$K = 4$:	SNR (dB)	$e_e = 0.05$	$e_e = 0.10$	$e_e = 0.15$
	-18	0.9893	1.9632	2.9758
	-16	1.0011	1.9692	2.9783
	-14	1.0043	1.9777	2.9988
	-12	1.0162	1.9790	2.9995
$K = 8$:	SNR (dB)	$e_e = 0.05$	$e_e = 0.10$	$e_e = 0.15$
	-18	1.0705	2.1687	3.2815
	-16	1.0856	2.1714	3.2818
	-14	1.0915	2.1769	3.3012
	-12	1.1056	2.1803	3.3042

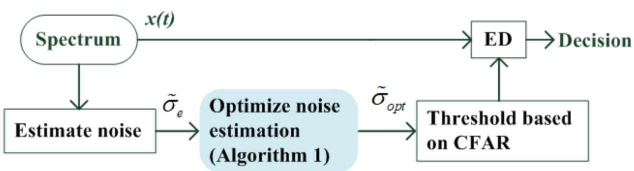


FIGURE 5. The flowchart of ONED-based spectrum sensing.

in (3) works well in such low SNR scenarios. The table also shows that the increases of both K and e_e degrade the performance of noise optimization, leading to larger e_{opt}.

Referring to Subsection III-B, it is required a low computational complexity of sensing. As the LP-based optimization is implemented by using Simplex algorithm for a small scale problem, the cost of optimization is not high. We test the experimental computation costs of the optimization procedure with 1000 Monte Carlo trials on the platform of MATLAB and obtain the following results:
a) When $K = 2$, for $e_e = 0.05$, 0.10 and 0.15, the average numbers of iterations are all 1, the time costs are between 1.7 ms and 2.0 ms.
b) When $K = 4$, for $e_e = 0.05$, 0.10 and 0.15, the average numbers of iterations are all 4, the time costs are between 2.3 ms and 2.5 ms.
c) When $K = 8$, for $e_e = 0.05$, 0.10 and 0.15, the average numbers of iterations are all 10, the time costs are between 4.3 ms and 4.5 ms.
The results show that the optimization can be converged by only several iterations and costs time in the order of ms, when the spectrum prediction provides a few possible holes for sensing.

3) EXPERIMENTAL PERFORMANCE OF ONED BASED SENSING

Based on the optimized estimation of noise variance, the ONED is proposed as shown in Figure 5 with the following steps:

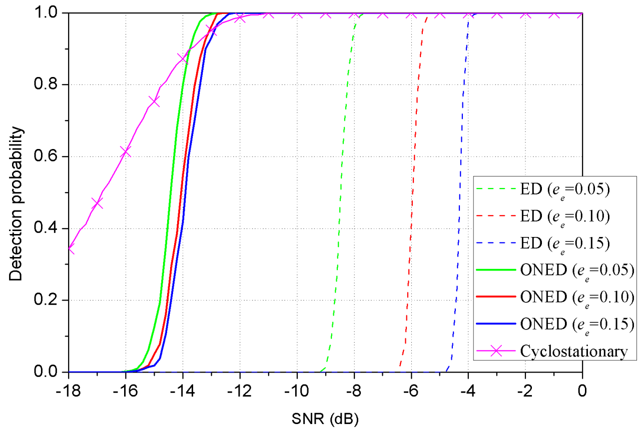


FIGURE 6. Simulation comparisons of spectrum sensing performance based on conventional ED, ONED and cyclostationary detection for BPSK signals by detection probability P_d ($K = 4$, $P_{fa} = 0.01$, $\epsilon = 0.001$).

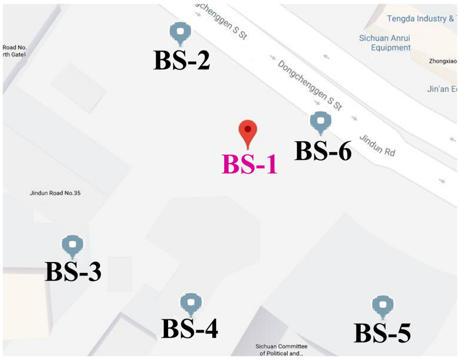
a) Estimate noise standard variances $\tilde{\sigma}_{e_k}$ for K sensing bands.

b) Optimize the estimated noise standard variances based on LP given in (3), and provide more accurate values $\tilde{\sigma}_{opt_k}$, following the steps as in Algorithm 1.

c) Compute the thresholds based on the optimized standard variances $\tilde{\sigma}_{opt_k}$, perform the ED for received signals, and make the decisions.

First we test the ONED-based sensing for a simulated BPSK signal with sample length $N_s = 8192$ for $K = 4$ by 10^4 Monte Carlo trials, comparing the detection probability P_d with other methods including the conventional ED and cyclostationary [2], [22] based sensing in Figure 6. The CFAR-based detection is adopted and $P_{fa} = 0.01$. It is observed that the proposed approach performs better than the conventional ED due to the optimization of noise estimation. For example, with the estimated error $e_e = 0.05$, the ONED detects the signal as $P_d \geq 0.95$ when SNR ≥ -13.6 dB while the conventional ED requires SNR ≥ -8 dB, improving over 5 dB. The cyclostationary based sensing considers the known signal detection, i.e., searching the peaks in the spectral correlation function of the input and comparing with those of the known signal. Therefore the cyclostationary based sensing could be supposed not related to noise power errors. Figure 6 shows that the ONED has similar performance as the cyclostationary based sensing when considering $P_d \geq 0.95$.

Next an experimental scenario will be tested. We consider the data provided by OpenCelliD which is the world's largest open database of cell towers and WiFi access points (available: opencellid.org) to select a region in City of Chengdu (China) including 6 BSs, shown in Figure 7. The latitudes and longitudes of BSs are available. We set BS-1 is the station whose bands would be accessed by UAV communication. Within 60 meters of the region of BS-1, there are 5 adjacent BSs as BS-2 $\sim$ 6. The parameters of BSs are height $=$ 50 m, power $=$ 43 dBm, bandwidth $=$ 20 MHz, and noise floor $= -100$ dBm. The mobile signals near a GSM-BS are measured and GMSK modulated signals are are



BS-1: Latitude: 30.655681, Longitude: 104.059263
BS-2: Latitude: 30.655975, Longitude: 104.059067
BS-3: Latitude: 30.655518, Longitude: 104.058609
BS-4: Latitude: 30.655289, Longitude: 104.059067
BS-5: Latitude: 30.655289, Longitude: 104.059753
BS-6: Latitude: 30.655746, Longitude: 104.059525

FIGURE 7. The selected region in City of Chengdu (China), showing the distribution of 6 BSs.

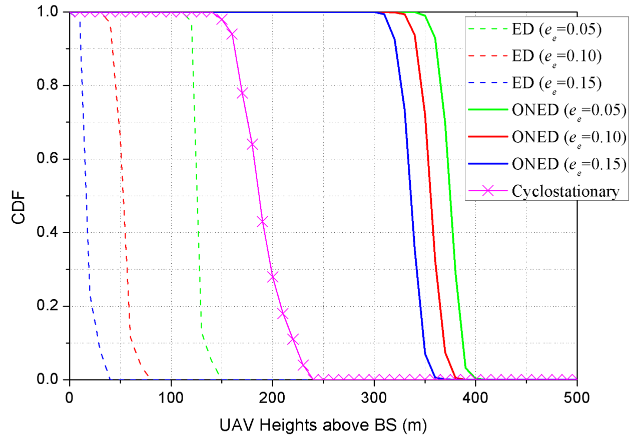


FIGURE 8. Experimental comparisons of spectrum sensing performance based on conventional ED, ONED and cyclostationary detection by CDF regarding to detection of the real GMSK signals ($K = 4$, $\epsilon = 0.001$, CFAR is used with $P_{fa} = 0.01$).

collected at the band of 953.8 MHz by using software defined radios. Then the GMSK signals were de-noised within SNR over 42 dB and down-converted into approximately clean baseband signals. The AWGN noise and errors ($e_e = 0.05$, 0.10 and 0.15) are preset and mixed in simulations. The loss of signal propagation is computed by the empirical formula: $Loss = 32.44+20\log_{10}(frequency)+20\log_{10}(distance)$. The sequence length of GMSK signal samples in each simulation is $N_s = 8192$ and constant $P_{fa} = 0.01$.

We test the ONED-based sensing for $K = 4$ by 10^4 Monte Carlo trials, shown in Figure 8. The performance is shown as cumulative distribution functions (CDF) calculated with 95% confidence intervals, regarding to the detection of GMSK signals. A higher value of CDF indicates better detection performance. It is observed that the proposed approach performs better than the conventional ED due to the optimization of noise estimation. For example, with the estimated error $e_e = 0.05$, the ONED has CDF > 0.9 when UAV height < 360 m while the conventional ED requires UAV height < 120 m, implying that the ONED-based UAV can work in higher/farther space. The performance of cyclostationary based sensing degrades mainly because the GMSK signal may not have the same cyclic autocorrelation property as the BPSK signal used in Figure 6. Comparing to the cyclostationary based sensing, the ONED could be applied on more types of signals since it does not require the signal has some certain properties.

It is worth to noted that the three curves based on the ONED for different e_e are closely distributed in both Figures 6 and 8, because all the values of optimized errors are quite small as in the order of 10^{-3}, which can be seen in Table 1 ($K = 4$). This implies that our method is always able to provide satisfied performance when the estimated error varies from 0.05 to 0.15. In another word, the ONED may be not very sensitive to the noise uncertainty while the conventional ED does.

The ONED works better than the conventional ED because the noise power estimation is improved by the optimization. An important reason why the noise power cannot be accurately estimated is that the statistics of noise in different frequency bands are not accurately evaluated. Usually, the conventional estimation theory is based on an assumption that the statistics of noise in different frequency bands are i.i.d. However, in practice, a strict i.i.d. property is generally not satisfied, resulting that the statistics of noise are difficult to be accurately evaluated. For example, the power of random signal and interference may leak into adjacent bands and affect the noise statistics. The proposed optimization uses a different view to solve this problem. We use a-prior information of some reserved bands which are usually unused to get a very accurate average noise level, to better infer the noise power of other bands. This is because the noise levels at different bands have the same background in a certain environment, as shown in Figure 4. Since the noise statistics in different bands are not independent, they should be optimized together, considering the effects of other bands.

B. CONSTANT MISSED DETECTION RATE BASED SENSING BY USING ONED

As we noted in Subsection III-D, to guarantee the UAV communications not to affect the primary user communications, it is required that the UAVs can always detect the primary signals in all situations with different SNRs. In a word, a method which can provide a low and constant missed detection rate is more suitable for the UAV communications than the CFAR based sensing, which is to keep the false alarm rate to be constant while the missed detection rate is varying at different SNRs [23]. We propose a CMDR based sensing approach to stably and reliably detect the primary signals at different SNRs by pre-setting a low missed detection rate P_{md}. This idea was firstly introduced in our previous conference paper [24]. Here we improve the formula derivation, verify the assumptions of distribution, and test using real practice signals. At last, the idea of CMDR is jointly used with the ONED to sense the GSM-BS signals of GMSK signals.

1) THE CMDR IN ED

For discrete signals with sample length N_s, the test statistics of ED introduced in (2) can be rewritten as

$$\gamma = \frac{1}{N_s} \sum_{n=1}^{N_s} x^2(n). \tag{5}$$

Under hypothesis H_0, γ follows a central chi-square distribution. As the random variables are i.i.d. and $N_s \gg 1$, by employing the central limit theorem, γ can be approximated as

$$H_0 : \gamma \sim N\left(\sigma^2, 2\sigma^4/N_s\right). \tag{6}$$

For H_1, we have

$$\begin{aligned}\gamma &= \frac{1}{N_s} \sum_{n=1}^{N_s} \left(s^2(n) + 2s(n)w(n) + w^2(n)\right) \\ &= \frac{1}{N_s} \sum_{n=1}^{N_s} s^2(n) + \frac{1}{N_s} \sum_{n=1}^{N_s} 2s(n)w(n) + \frac{1}{N_s} \sum_{n=1}^{N_s} w^2(n).\end{aligned}$$

When the sampling duration is much longer than the signal symbol period, the first term of above equation can be approximated to be the signal average power σ_s^2. For the second term, assuming $s(n)$ is a known signal, we have

$$s(n)w(n) \sim N\left(0, s^2(n)\sigma^2\right), \tag{7}$$

resulting as

$$\frac{1}{N_s} \sum_{n=1}^{N_s} 2s(n)w(n) \sim N\left(0, 4\sigma_s^2\sigma^2/N_s\right). \tag{8}$$

The last term is actually the test statistic under H_0 and has the same result as (6). Also by employing the central limit theorem, γ is approximated as

$$H_1 : \gamma \sim N\left(\sigma^2 + \sigma_s^2, \left(2\sigma^4 + 4\sigma_s^2\sigma^2\right)/N_s\right). \tag{9}$$

We verify this distribution by using a GMSK signal and AWGN noise. Figure 9 shows the distribution of decision statistic with 12000 Monte Carlo simulations when we set the signal power equaling to 0.5 and the noise power equaling to 0.5. It is observed that the distribution assumption in (9) is highly consistent with the fact since the normalized mean square errors (MSEs) of simulation and Gaussian distributions are quite small at different SNRs. Therefore, the missed detection P_{md} can be obtained as

$$P_{md} = 1 - Q\left(\frac{V_T - \sigma^2 - \sigma_s^2}{\sqrt{\left(2\sigma^4 + 4\sigma^2\sigma_s^2\right)/N_s}}\right), \tag{10}$$

where $Q(\cdot)$ is the Gaussian tail probability Q-function. When P_{md} is preset as a constant, the threshold V_T can be calculated as

$$V_T = \sigma^2 + \sigma_s^2 + Q^{-1}(1 - P_{md}) \sqrt{\left(2\sigma^4 + 4\sigma^2\sigma_s^2\right)/N_s}, \tag{11}$$

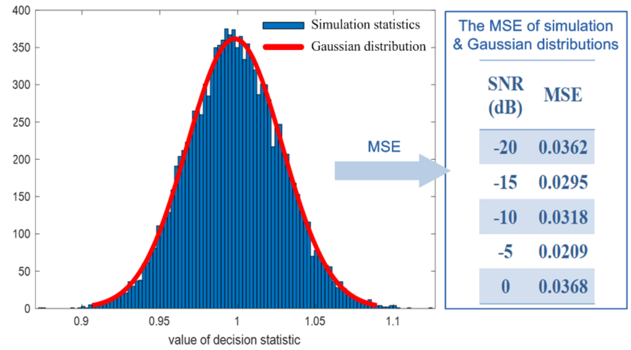


FIGURE 9. Comparison of the simulated test statistic distribution and the theoretical Gaussian distribution.

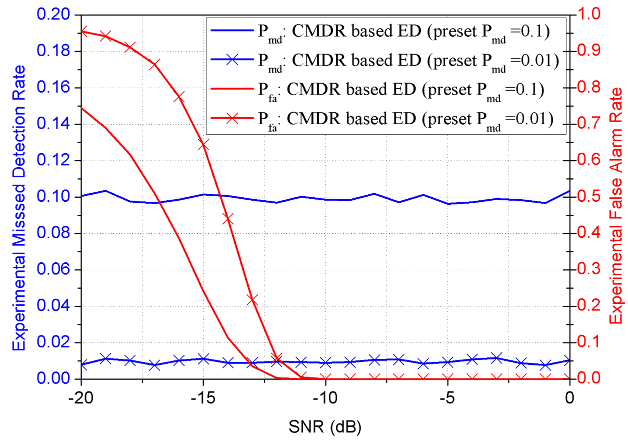


FIGURE 10. Experimental missed detection and false alarm rates by using the conventional ED based on the CMDR when P_{md} is preset as 0.1 and 0.01, without noise estimation errors (GMSK, $N_s = 8192$, 10^4 Monte Carlo tests).

and the false alarm rate

$$P_{fa} = Q\left(\left(V_T - \sigma^2\right)/\sqrt{2\sigma^4/N_s}\right). \tag{12}$$

Figure 10 presents the detection results by using the conventional ED using the CMDR based thresholds. This figure has double Y-axes that the two blue curves of P_{md} correspond to the left Y-axis and the two red curves of P_{fa} correspond to the right Y-axis. It is observed that the experimental missed detection rates are tightly around the preset $P_{md} = 0.1$ and 0.01, indicating that the CMDR based ED can work well at different SNRs. The false alarm rates are varying when the SNR is changing. For low SNRs, a lower presetting P_{md} makes P_{fa} increase.

It is noted that the CMDR based ED requires a-prior information including signal and noise power. The simulation in previous figure does not consider the estimation errors of signal and noise power. If the noise power is not accurately estimated, the optimization procedure of noise power introduced in Subsection IV-A may be also useful for the CMDR based ED. Therefore, a joint use of CMDR and ONED will be

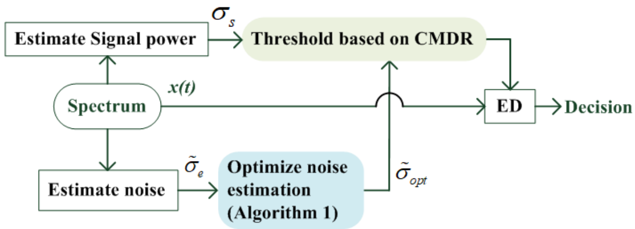


FIGURE 11. The flowchart of ONED-based spectrum sensing using CMDR based decision.

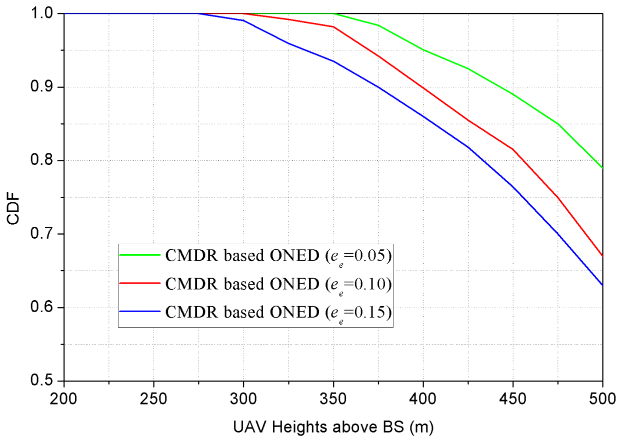


FIGURE 12. Experimental comparisons of spectrum sensing performance based on conventional ED and ONED with CMDR by CDF regarding to detection of the real GMSK signals ($K = 4$, $P_{md} = 0.02$, $\epsilon = 0.001$).

presented in the following content to implement the spectrum sensing for UAV communications.

2) EXPERIMENTAL PERFORMANCE OF THE CMDR BASED ONED

We modify the decision rule in Subsection IV-A by using the CMDR concept instead of the CFAR, to sense the same space environments as used in Figure 8. The sensing procedure is shown in Figure 11. Comparing to Figure 5, this sensing approach adopts the CMDR rule to compute the threshold used in ED decision.

Figure 12 illustrates the experimental sensing performance of ONED in sense of CMDR where P_{md} is preset as 0.02. The experimental scenario is the same as in Figure 8. It is observed that the proposed CMDR-ONED is able to effectively sense signals when the user heights are not high. Comparing to the CFAR based ONED approach in Figure 8, the CMDR base sensing may perform better when the heights are higher, since the CMDR based method uses more a-prior information than the CFAR based method. For instance, the CFAR based ONED can not work when the height $>$ 400, while the CMDR based ONED could partially work.

V. CONCLUSION

This paper introduced opportunistic spectrum access for UAV communications, including brief reviews of UAV, satellite and terrestrial communications. It was explained that spectrum management should be employed for UAV communications to avoid interference. Two main challenges were referred: one is that the processing algorithms are required to be fast since the UAVs transfer different spectrum environments very quickly; another one is that the spectrum prediction should be based on the joint information of temporal-spatial dimension. Other issues such as the MSR and constant missed rate based detection were also discussed.

A fast approach of spectrum sensing for UAVs was proposed in the paper. It introduced a new perspective to improve the ED performance by the LP-based optimization which greatly suppressed the estimated error of noise variance, without requiring high additional computation. For different degrees of noise estimation errors, it was observed that the ONED always provided good performance from simulated results, implying that our proposed approach might not be very sensitive to the noise uncertainty. Besides, the CMDR based decision rule is able to ensure the detection performance of primary signals. Although we used the scenario of terrestrial BSs to test, the proposed approach can be also applied for UAVs in other environments illustrated in Figure 1 such as UAV-HAP scenarios.

REFERENCES

[1] Y. Zeng, R. Zhang, and T. J. Lim, "Wireless communications with unmanned aerial vehicles: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 54, no. 5, pp. 36–42, May 2016.

[2] A. Ali and W. Hamouda, "Advances on spectrum sensing for cognitive radio networks: Theory and applications," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 1277–1304, 2nd Quart., 2016.

[3] Y. Teng, M. Liu, F. R. Yu, V. C. M. Leung, M. Song, and Y. Zhang, "Resource allocation for ultra-dense networks: A survey, some research issues and challenges," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2134–2168, 3rd Quart., 2019.

[4] H. Wang, G. Ding, F. Gao, J. Chen, J. Wang, and L. Wang, "Power control in UAV-supported ultra dense networks: Communications, caching, and energy transfer," *IEEE Commun. Mag.*, vol. 56, no. 6, pp. 28–34, Jun. 2018.

[5] G. Ding, Y. Jiao, J. Wang, Y. Zou, Q. Wu, Y. Yao, and L. Hanzo, "Spectrum inference in cognitive radio networks: Algorithms and applications," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 1, pp. 150–182, 1st Quart., 2018.

[6] E. Chatziantoniou, B. Allen, V. Velisavljevic, P. Karadimas, and J. Coon, "Energy detection based spectrum sensing over two-wave with diffuse power fading channels," *IEEE Trans. Veh. Technol.*, vol. 66, no. 1, pp. 868–874, Jan. 2017.

[7] A. Sonnenschein and P. M. Fishman, "Radiometric detection of spread-spectrum signals in noise of uncertain power," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 28, no. 3, pp. 654–660, Jul. 1992.

[8] C.-Y. Chi, W.-C. Li, and C.-H. Lin, *Convex Optimization for Signal Processing and Communications: From Fundamentals to Applications*. Boca Raton, FL, USA: CRC Press, 2017.

[9] F.-Y. Wang, C.-Y. Chi, T.-H. Chan, and Y. Wang, "Nonnegative least-correlated component analysis for separation of dependent sources by volume maximization," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 5, pp. 875–888, May 2010.

[10] S. Zhang, H. Zhang, B. Di, and L. Song, "Cellular UAV-to-X communications: Design and optimization for multi-UAV networks," *IEEE Trans. Wireless Commun.*, vol. 18, no. 2, pp. 1346–1359, Jan. 2019.

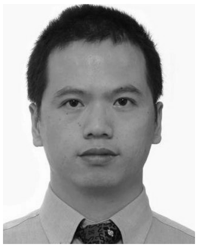
[11] X. Cao, P. Yang, M. Alzenad, X. Xi, D. Wu, and H. Yanikomeroglu, "Airborne communication networks: A survey," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 10, pp. 1907–1926, Sep. 2018.

[12] W.-Q. Wang and D. Jiang, "Integrated wireless sensor systems via near-space and satellite platforms: A review," *IEEE Sensors J.*, vol. 14, no. 11, pp. 3903–3914, Nov. 2014.

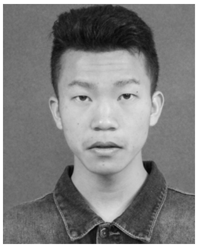
[13] S. Maleki, S. Chatzinotas, B. Evans, K. Liolis, J. Grotz, A. Vanelli-Coralli, and N. Chuberre, "Cognitive spectrum utilization in Ka band multi-beam Satellite communications," *IEEE Commun. Mag.*, vol. 53, no. 3, pp. 24–29, Mar. 2015.
[14] M. Jia, X. Gu, Q. Guo, W. Xiang, and N. Zhang, "Broadband hybrid satellite-terrestrial communication systems based on cognitive radio toward 5G," *IEEE Wireless Commun.*, vol. 23, no. 6, pp. 96–106, Dec. 2016.
[15] C. Zhang, C. Jiang, L. Kuang, J. Jin, Y. He, and Z. Han, "Spatial spectrum sharing for satellite and terrestrial communication networks," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 55, no. 3, pp. 1075–1089, Jun. 2019.
[16] X. Xing, T. Jing, W. Cheng, Y. Huo, and X. Cheng, "Spectrum prediction in cognitive radio networks," *IEEE Wireless Commun.*, vol. 20, no. 2, pp. 90–96, Apr. 2013.
[17] Y. Zhao, Z. Hong, Y. Luo, G. Wang, and L. Pu, "Prediction-based spectrum management in cognitive radio networks," *IEEE Syst. J.*, vol. 12, no. 4, pp. 3303–3314, Dec. 2018.
[18] D. López-Pérez, M. Ding, H. Claussen, and A. H. Jafari, "Towards 1 Gbps/UE in cellular systems: Understanding ultra-dense small cell deployments," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2078–2101, 4th Quart., 2015.
[19] Y. Li and S. K. Jayaweera, "Dynamic spectrum tracking using energy and cyclostationarity-based multi-variate non-parametric quickest detection for cognitive radios," *IEEE Trans. Wireless Commun.*, vol. 12, no. 7, pp. 3522–3532, Jul. 2013.
[20] X. Chen, H. Zhang, A. B. MacKenzie, and M. Matinmikko, "Predicting spectrum occupancies using a non-stationary hidden Markov model," *IEEE Wireless Commun. Lett.*, vol. 3, no. 4, pp. 333–336, Aug. 2014.
[21] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proc. IEEE*, vol. 55, no. 4, pp. 523–531, Apr. 1967.
[22] M. Kumar and R. Dabora, "A novel sampling frequency offset estimation algorithm for OFDM systems based on cyclostationary properties," *IEEE Access*, vol. 7, pp. 100692–100705, 2019.
[23] L. Sevgi, "Hypothesis testing and decision making: Constant-false-alarm-rate detection," *IEEE Antennas Propag. Mag.*, vol. 51, no. 3, pp. 218–224, Jun. 2009.
[24] X. Xie, S. Luo, R. Lin, and J. Huang, "A constant missed detection rate based spectrum sensing for UAV communications towards ultra-dense networks," in *Proc. 10th Int. Conf. Commun., Circuits Syst. (ICCCAS)*, Dec. 2018, pp. 320–324.

SHAN LUO received the bachelor's degree in electrical information engineering and master's degree in signal and information processing from the University of Electronic Science and Technology of China, in 2007 and 2010, respectively, and the Ph.D. degree in information engineering from Nanyang Technological University, in 2014. She is currently an Associate Professor with the School of Aeronautics and Astronautics, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. Her research interests include wireless communications, signal processing, and time-frequency analysis.

YONG XIAO (S'09–M'13–SM'15) received the B.S. degree in electrical engineering from the China University of Geosciences, Wuhan, China, in 2002, the M.Sc. degree in telecommunication from the Hong Kong University of Science and Technology, in 2006, and the Ph.D. degree in electrical and electronic engineering from Nanyang Technological University, Singapore, in 2012. He is currently a Professor with the School of Electronic Information and Communications, Huazhong University of Science and Technology, Wuhan, China. His research interests include machine learning, game theory, and their applications in wireless networks.



RONGPING LIN received the Ph.D. degree from the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, in 2013. He is currently an Associate Professor with the School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. His research interests include communications, optical networks, and SDN networks.



XIANGDONG XIE is currently pursuing the bachelor's degree with the School of Aeronautics and Astronautics, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. His research interests include wireless communications and signal detection.

GUOAN BI was born in 1954. He received the bachelor's degree in radio communications from the Dalian University of Technology, China, in 1982, the master's degree in telecommunication systems and Ph.D. degree in electronics systems, Essex University, U.K., in 1985 and 1988, respectively. He is currently an Associate Professor with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore. His research areas include computational fast algorithm, time-frequency analysis, signal detection, and parameter estimation for applications in communications, radar and sonar systems.

YUWEI ZHAO is currently pursuing the master's degree with the School of Aeronautics and Astronautics, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. His research interests include communications and signal processing.

JIYAN HUANG is currently an Associate Professor with the School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. His research interests include radar, signal processing, and communications.