Optimisation of virtual cooperative spectrum sensing for UAV-based interweave cognitive radio system

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Abstract

In an interweave cognitive radio system, cooperative spectrum sensing has been recognised as a key technology to enable secondary users to opportunistically access licensed spectrum band without harmful interference to primary users. At the same time, the unmanned aerial vehicle equipped with spectrum sensing and data transmission facilities is gaining more popularity in different applications. An unmanned aerial vehicle-based interweave cognitive radio is investigated in which the unmanned aerial vehicle is used as a secondary user, but unlike the participation of multiple secondary users in traditional cooperative spectrum sensing, a virtual cooperative spectrum sensing model is introduced into the periodic spectrum sensing frame structure. Afterwards, the authors further propose an energy-efficient virtual cooperative spectrum sensing with the sequential 0/1 fusion rule to reduce the average number of decisions without any loss in the detection performance. Sequentially, the authors formulate the optimisation of virtual cooperative spectrum sensing for unmanned aerial vehicle-based interweave cognitive ratio system as the optimal sequential 0/1 fusion problem on the basis of the K-out-of-N fusion rule and prove the formulated problem indeed has one optimal K, which yields the highest throughput. Finally, numerical simulations are presented to demonstrate the correctness of theoretical analyses and the effectiveness of the virtual cooperative spectrum sensing with the sequential 0/1 fusion rule.

1 | INTRODUCTION

With the increasing use of wireless services for various applications (i.e. unmanned aerial vehicle (UAV) communications), dynamical access to a limited wireless spectrum has become critical and increasing demands in technology. However, current wireless spectrums are managed by a fixed spectrum assignment policy [1], wherein a large portion of spectrum is already assigned to primary users (PUs) but is greatly under-utilised either temporally or spatially. For this reason, cognitive radio (CR) technology is proposed to allow secondary users (SUs) to be aware of internal state and environment of the PUs’ communication system, such as location and utilisation of radio frequency (RF) spectrum. The utilisation of this element is critical in allowing SUs to make use of available frequency spectrum with a common set of radio hardware. The CR continuously senses the holes in the spectrum, which can be seized by SUs for its use [1].

In this regard, the ability of CR technology to intelligently use spectrum dynamically offers a new approach to existing unmanned aerial vehicles (UAVs). For example, Bostian and Young [2] investigated the capability of CRs based on the GNU (an operating system of free software) radio/universal software radio peripheral open-source platform to meet the needs of the UAVs of interest, and Stamatescu et al. [3] introduced a new framework and system architecture for multi-level heterogeneous monitoring and surveillance based on ground-aerial
In other words, UAVs can greatly benefit from the integration with CR technology by considering the advantages that this technology brings, such as dynamic spectrum access, reduced energy consumption and delay, opportunistic use of spectrum based on applications requirements [4]. There are also significant gains regarding reliability of UAV networks [5, 6]. Hence, UAV-based CR could be used in critical applications (e.g. weather monitoring and disaster management and wildfire monitoring) or in circumstances where dynamic spectrum access can be used for either overcoming overcrowded radio spectrum or for opportunistic spectrum usage based on applications requirements [4].

### 1.1 Related works

However, the integration of CR and UAVs imposes many issues which are due to the intrinsic characteristics of CR and UAVs [7]. In the CR system, cooperative spectrum sensing (CSS) is the most important function to detect the spectrum holes for SUs and opportunistically access the idle channel under-utilised by the PUs. Other spectrum management functions rely on this function in order to perform their tasks. For this aim, Liang et al. [8] considered MAC frame structure design supporting periodic spectrum sensing and formulated the sensing-throughput trade-off problem by considering the interest of both PUs and SUs. Particularly, the authors studied the problem of designing the sensing slot duration to maximise the achievable throughput for the SUs under the constraint that the PUs are sufficiently protected. Mishra [9] focused on a spatial perspective and advanced algorithms to maximise the recovery of unused spectrum. Nieminen et al. [10] studied the performance of overlapping CR networks (CRNs) which co-exist with a PU. The performance of CRNs in such situations was evaluated by investigating the achievable per-node throughput. Chen et al. [11] studied the spectrum sharing based on joint spatial-temporal sensing with PU interference constraint. For CRNs with periodic spectrum sensing, there exists a trade-off between sensing capability and achievable throughput of secondary system. The optimal sensing time was derived to maximise the throughput of secondary system. Wu et al. [12] formulated a joint spatial and temporal opportunity detection model. On the basis of this model, the authors further analysed and compared the detection performance of the traditional non-cooperative sensing and cooperative sensing (CS) schemes at both the user level and network level. The above-mentioned works on the CSS problem of CR provide the necessary infrastructure for the realisation of UAV communication systems.

On the basis of CR technology, Sboui et al. [13] studied the achievable rate of an uplink multiple input multiple output (MIMO) CR system where the PU and the SU aim to communicate to the closest primary base station via a multi-access channel through the same UAV relay. Ghazzai et al. [14] integrated CR technology with micro UAV (MUAV) and developed an energy-efficient optimisation problem for the underlay technique. Sharma et al. [15] studied a hybrid satellite-terrestrial spectrum sharing system (HSTSSS) in which multiple terrestrial secondary networks cooperate with a primary satellite network for dynamic spectrum access. For complexity-aware HSTSSS design, the authors proposed an amplify-and-forward-based secondary network selection schemes. Like in [13–15], many efforts have been devoted to studying the overlay or underlay CR model, but the interweave CR model has been ignored. For the mission-critical communication scenarios (e.g. commercial drones, border patrolling, crop monitoring, and traffic surveillance), the interweave operation mode is the preferred cognitive operation mode. In the interweave mode, the SUs perform spectrum sensing to detect the PU activity. The legacy UAV communication hardware need not be altered, which guarantees a smooth transition of legacy systems into CR-based systems [16].

Furthermore, Zhang et al. [17] considered an uplink network model with an UAV working as an amplify- and-forward relay, and optimised the trajectory of UAV, the transmit power of UAV, and the mobile device by minimising the outage probability of this relay network. A two-stage fusion scheme was proposed in [18] to perform fast information fusion, which can remarkably reduce the number of information exchanges, and hence enhance the spectrum sensing performance of cognitive UAV networks. Hongwei et al. [19] proposed a fast and efficient CSS algorithm for large cognitive UAV network, which can minimise the number of UAVs participating in CSS to assure that the total detection error rate is less than a certain threshold. An UAV-based CR was proposed to improve spectrum sensing performance and maximise the effective throughput of the UAV by optimising the sensing duration subject to the interference throughput constraint in [20]. Pan et al. [21] proposed an efficient energy management solution to improve the performance of the UAV. When SUs opportunistically utilise the licensed spectrum of the primary network, spectrum sensing is needed to determine whether to transmit data or not, so the sensing time and secondary transmission power should be jointly optimised. Shen et al. [22] investigated the issue of joint spatial-temporal spectrum sensing in 3D spectrum-heterogeneous space by leveraging the location flexibility of flying UAV spectrum sensors. Afterwards, the authors designed a temporal fusion window and a spatial fusion sphere to address the composite spatial-temporal data fusion, called 3D spatial-temporal sensing.

Though the above-mentioned references consider the CSS optimisation for UAV-based CR system to improve the detection performance and maximise the effective throughput, they ignore the fact that the CSS process requires the large communication resource for processing decisions about the PU activity [23]. The benefits that CSS brings with are at the cost of high overhead, such as control channel bandwidth, energy consumption, and reporting delay, which limits or even compromises the available cooperative gain. When the UAV is energy constraint (e.g. battery-powered), energy efficiency is an important issue for CSS. Energy consumption in CSS generally involves in the number of decisions required at the PU state decision-making [24]. It can be seen that ignoring the impact of the number of decisions on CSS to optimise the performance or throughput is arbitrary for a UAV-based CR system.
1.2 | Our contributions

In summary, the energy efficiency and achievable throughput are critical and challenging issues in UAV-based CR systems. To address this problem, this paper makes three major contributions as follows:

- Benefiting from the advantages of the interweave model, an UAV-based interweave CR is investigated in which the UAV is used as a SU, but unlike the participation of multiple SUs in traditional CSS (TCSS), we introduce a virtual cooperative spectrum sensing (VCSS) into the periodic spectrum sensing frame structure of a UAV.
- Considering the energy efficiency issue of CSS, based on the hard-combining and the $K$-out-of-$N$ rule, we propose a VCSS with the sequential 0/1 fusion (SZOF) rule, which results in less decisions for decision-making and avoids consuming too much communication resource. Further, we verify that the detection performance of the SZOF rule is completely the same as that of conventional decision fusion (CDF) rule.
- We formulate the optimisation of VCSS for UAV-based interweave CR system as the optimal SZOF problem on the basis of the $K$-out-of-$N$ fusion rule and prove the formulated problem indeed has one optimal $K$ which yields the highest throughput.

1.3 | Organisation

The remainder of this paper is organised as follows. In Section 2, the system model is introduced. Then, the performance metric and performance analysis of VCSS with the CDF rule are presented in Section 3. Further, Section 4 provides the performance metric and performance analysis of VCSS with the SZOF rule. The optimisation problem of VCSS is formulated and analysed in Section 5. In Section 6, the comparison results are simulated. Conclusion is drawn in Section 7.

2 | SYSTEM MODEL

2.1 | UAV-based interweave CR model

Motivated by the mobile CR network model of [25], we extend two-dimensional (2D) spectrum sensing of [25] to 3D spectrum sensing by the UAV spectrum sensor. We consider a UAV-based interweave CRN as shown Figure 1, in which a PU locates at the centre and some UAVs. The UAVs (are regarded as SUs) sense the presence or absence of the PU by the local spectrum sensing (LSS) techniques. The sensing radius is denoted by $R_s$, the UAV cannot sense the PU if the distance between the PU and UAV is greater $R_s$, whereas the UAVs are not allowed to sense the PU in the range of the protected radius $R_p$ in order to avoid the harmful interference to its normal operation. In other words, the UAVs can detect the PU signal only in the ring of 3D space and then access the idle channel that is not utilised by the PU.

There is no doubt that the UAV has promising potential to explore and exploit spectrum opportunity in 3D spectrum space by properly leveraging the location flexibility of flying UAV spectrum sensors. Though the UAVs outside the range of the sensing radius or inside the range of the protected radius cannot participate in the spectrum sensing, they can still achieve dynamic spectrum sharing through other UAV relays. In addition, our goal is to achieve the highest throughput of the UAV-based interweave CRN by means of a specific fusion rule in CSS. Except for the spectrum sensing time in a frame structure, the data transmission time for UAV service is the focus of our research.

Hence, we take a UAV in the network model as example. Similar to [19], the UAV makes a circular flight around a PU, as shown in Figure 2. The flight radius is $r$, the flight altitude is $b$ (the antenna height of the PU is negligible), then the sensing distance can be expressed as follows:

$$ s = \sqrt{r^2 + b^2} \tag{1} $$

where $R_p \leq s \leq R_s$. 
2.2 VCSS model

![Virtual cooperative spectrum sensing in the periodic spectrum sensing frame structure](image1)

In an UAV-based interweave CR system, the UAV makes use of the spectrum sensing technique to detect the spectrum holes, and then transmits if and only if the PU is absent. In contrast to the ground spectrum sensing, the channel from the UAV-based CR to the ground PU can be seen as line of sight (LOS); thus, the detection performance degradation caused by the severe ground fading can be ignored in the UAV spectrum sensing. That is to say, the single-user spectrum sensing may achieve better detection performance in the UAV environment than in the ground environment, because the UAV can receive a higher strength signal without suffering severe fading and shadowing. Hence, a UAV is used for spectrum sensing because of the cost reduction.

2.3 LSS performance

![Unmanned aerial vehicle flight model](image2)

To realise VCSS, now we consider the LSS performance in a mini-slot. Existing LSS technologies include matched filter, energy detection, cyclostationary detection, and wavelet detection. Among these LSS technologies, the energy detection is commonly adopted because of its low complexity and also it does not require any prior knowledge of the PU signal. In the energy detection, the PU is usually formulated as a binary hypothesis test problem [25], then the LSS model for the \( i \)th mini-slot is described as follows:

\[
\begin{align*}
    y_i(m) &= u_i(m), \quad H_0 \\
    y_i(m) &= g(k)s_i(m) + u_i(m), \quad H_1
\end{align*}
\]

where \( H_0 \) and \( H_1 \) respectively represent the hypothesis on the presence and absence of the PU signal. The UAV’s received signal \( s_i(m) \) transmitted by the PU is distorted by the channel gain \( g(k) \) at the \( k \)th frame, \( u_i(m) \) denotes the circularly symmetric complex Gaussian noise. Without loss of generality, \( s_i(m) \) and \( u_i(m) \) are assumed to be independent [26].

Consider the PU signal transmitted through free space to the UAV receiver located at the sensing distance \( s \) from the PU transmitter. Assume there are no obstructions between the transmitter and receiver and that the signal propagates along a circular flight between the two. The channel model associated with this transmission is a LOS channel [27], then \( g(k) = \xi / s \), where \( \xi = c / (4\pi f_s) \) denotes the channel gain at the unit distance, \( f_s \) is the sampling frequency [28].
The test for energy detector is calculated as follows:

$$E_i (y) = \sum_{m=1}^{M} |y_{i}(m)|^2$$  \hspace{1cm} (6)

where $M$ is the number of samples. For a large $M$, using central limit theorem, we have the following probability density function of $E_i (y)$

$$E_i (y) \sim \begin{cases} N \left( \mu_0, \sigma_0^2 \right) & H_0 \\ N \left( \mu_1, \sigma_1^2 \right) & H_1 \end{cases}$$  \hspace{1cm} (7)

where $\mu_0 = M\sigma_0^2$, $\sigma_0^2 = 2M\sigma_s^4$ and $\mu_1 = M(\gamma + 1)\sigma_0^2$, $\sigma_1^2 = 2M(\gamma + 1)^2\sigma_s^4$, $\gamma = \frac{\sigma_s^2}{\sigma_0^2}$ is the average signal-noise-ratio (SNR) of the PU measured at the mini-slot of interest.

In the LSS, the local false alarm and detection probability for each mini-slot are assumed to be the same, which are calculated by comparing the local measured energy with a predefined energy threshold $\lambda$ and can be obtained as follows: [8]

$$P_f = P \left( E_i (y) > \lambda H_0 \right) = Q \left( \frac{\lambda}{\sigma_0^2} - 1 \right) \sqrt{\tau_{i,f_i}}$$  \hspace{1cm} (8)

$$P_d = P \left( E_i (y) > \lambda H_1 \right) = Q \left( \frac{\lambda}{\sigma_1^2 (\gamma + 1)} - 1 \right) \sqrt{\tau_{i,f_i}}$$  \hspace{1cm} (9)

where $Q(\cdot)$ is the complementary distribution function of the standard Gaussian.

### 3 \ VCSS WITH CDF RULE

With the aim of proposing an energy-efficient VCSS, we start with analysing the CDF rule based on the $K$-out-of-$N$ rule and its average number of decisions, the detection performance.

#### 3.1 \ CDF rule

In TCSS, multiple SUs submit their sensing results to a central entity, called fusion centre (FC), which is in charge of issuing a final/global decision about the spectrum occupancy based on a specific fusion rule. As one of the simplest data fusion technologies [29], the $K$-out-of-$N$ rule is available for the FC to make the global decision, which represents that more than $K$ decisions report the presence of the PU, then the FC broadcasts the channel is busy.

Similar to TCSS, the functionality of the global decision making about the PU status at each frame should also be considered in VCSS. Based on the $K$-out-of-$N$ rule, the traditional multi-user CSS method is replaced by multiple slots CS of a single user in our proposed UAV-based interweave CR system. Each mini-slot in VCSS with the CDF rule needs to perform LSS before CSS is completed, and then the UAV outputs a binary decision. Because the VCSS model does not have a powerful FC to fuse binary decisions from $N$ mini-slots [30], binary decisions from $N$ mini-slots are fused based on the $K$-out-of-$N$ rule within the sensing slot.

Following the $K$-out-of-$N$ rule, the global decision of the CDF rule can be described as follows:

$$F (k) = \begin{cases} \sum_{i=1}^{N} r_i \geq K, \text{ accept } H_1 \\ \sum_{i=1}^{N} r_i < K, \text{ accept } H_0 \end{cases}$$  \hspace{1cm} (10)

where $F(k)$ represents the global detection at the $k$th frame, $r_i$ represents the local decision of the $i$th mini-slot.

Apparently, multiple mini-slots CSS that exploits the spatial diversity in VCSS effectively relaxes the sensitivity requirements on individual mini-slot and improves the overall detection performance. In fact, there is no need for a powerful FC because it occurs spectrum sensing costs in UAV-based interweave CR system [30]. Next, we further investigate the average number of decisions and the detection performance of the CDF rule.

#### 3.2 \ Average number of decisions of CDF rule

From the above description, the $K$-out-of-$N$ rule is realised in low complexity without any prior knowledge on the PU signal. But one obvious drawback is that no matter what kind of the decision threshold $K$ is adopted in each frame, for an energy constraint UAV, a fixed number of decisions $N$ is required to inefficiently make the global decision about the PU status. In other words, the number of decisions is always $N$.

Although multi-slot CSS brings improved detection performance, it comes at the cost of high overhead, such as control channel bandwidth, energy consumption, and reporting delay, which limits or even compromises the available cooperative gain. Considering that the UAV is energy constraint, energy efficiency is an important issue in VCSS and should be considered.

#### 3.3 \ Detection performance of CDF rule

Based on the $K$-out-of-$N$ rule, the global false alarm probability and detection probability of VCSS with the CDF rule can be obtained as follows:

$$Q_{f,c} (K) = \sum_{j=K}^{N} \left( \begin{array}{c} N \\ j \end{array} \right) P_f^j (1 - P_f)^{N-j}$$  \hspace{1cm} (11)

$$Q_{d,c} (K) = \sum_{i=K}^{N} \left( \begin{array}{c} N \\ i \end{array} \right) P_d^i (1 - P_d)^{N-i}$$  \hspace{1cm} (12)
4 | VCSS WITH SZOF RULE

In view of disadvantages of the CDF rule, it is necessary to propose an energy-efficient VCSS for a UAV-based interweave CR system. Encouraged by the sequential idea, we integrate the sequential detection into the CDF rule to reduce the number of decisions in this section, resulting in the improvement in energy efficiency of VCSS. The main advantage of the sequential detection is that it requires, on an average, fewer decisions to achieve the same detection performance as the fixed number of decisions [30].

4.1 | SZOF rule

In the SZOF rule, the local decisions from mini-slots are sequentially processed at each sensing slot until a global decision outputs according to the $K$-out-of-$N$ rule. In details, a binary decision $r_i$ of the first mini-slot is compared with the decision threshold $K$ after the LSS is implemented, $H_1$ is accepted if $r_i$ is greater or equal to $K$, the spectrum sensing is suspended, the UAV needs to switch another channel and continue sensing, otherwise the UAV is allowed to access the channel at the data transmission slot. Consequently, the LSS of the second mini-slot proceeds and outputs a binary decision $r_2$, and the sum $r_1 + r_2$ of the two binary decisions are still compared with $K$. Similarly, if $\sum_{i=1}^{N} r_i$ is still less than $K$ until $i = N$, then the global decision is automatically 0, otherwise the global decision is 1, the UAV is allowed to access the channel.

Through the above description about the SZOF rule, the sequential process of the $k$th frame is described as Equation (13), where $k$ varies from 1 to $N$.

4.2 | Average number of decisions of SZOF rule

The next thing comes into consideration is the average number of decisions required at the SZOF rule. Assume that $P_k$ denotes the probability of the local decision 1 for a mini-slot, thus the average number of decisions to satisfy the $K$-out-of-$N$ rule can be obtained by

$$\psi(N, K, P_k) = \sum_{i=1}^{N} \phi(i, K, P_k) + \phi(i, N - K + 1, 1 - P_k)$$

where $\phi(w, u, p) = \binom{w-1}{u-1} p^u (1 - p)^{w-u}$ denotes the probability of negative binomial distribution. When the global decision is made, there must be either $K$ decision 1s or $N - K - 1$ decision 0s, thus

$$\sum_{i=1}^{N} \phi(i, K, P_k) + \phi(i, N - K + 1, 1 - P_k) = 1$$

The left hand side of Equation (15) is the sum of the global detection probability $Q_{g,K}(K)$ and the global miss detection probability $Q_{m,K}(K)$, and certainly equals to 1 as the right hand side (RHS). Therefore, $\phi(N, K, P_k) \leq N$ implies that VCSS with the SZOF rule requires a smaller average number of decisions.

According to the Bayes theorem, the average number of decisions can be given as follows:

$$A(K) = \phi(N, K, P_k) P(H_0) + \phi(N, K, P_0) P(H_1)$$

$$= \binom{N - 1}{K - 1} P_j^K (1 - P_j)^{N - K} P(H_0)$$

$$+ \binom{N - 1}{K - 1} P_d^K (1 - P_d)^{N - K} P(H_1)$$

where $P(H_0)$ and $P(H_1)$ represent the probability of the hypothesis $H_0$ and $H_1$, respectively.

Because the application of the SZOF rule reduces the number of decisions for the global decision making, the energy efficiency of the CSS process is improved. For a fixed frame duration, $\tau$, the reduction of the number of decisions means that the sensing time $A(K) \tau$ is shortened and the data transmission time $\tau_d$ of the UAV is extended.

4.3 | Detection performance of SZOF rule

Relying on the SZOF rule, the global false alarm probability and detection probability are, respectively, given as follows:

$$Q_{f,K}(K) = \binom{N}{i} \binom{i - 1}{K - 1} P_j^K (1 - P_j)^{i - K}$$

$$Q_{d,K}(K) = \binom{N}{i} \binom{i - 1}{K - 1} P_d^K (1 - P_d)^{i - K}$$

Because the SZOF rule does not change the decision threshold $K$, it can provide the same detection performance
as well as the CDF rule in theory. The following is presented as a brief analysis to the detection performance of the SZOF rule.

**Proposition 1.** The detection performance of VCSS with SZOF rule is the same as that of VCSS with CDF rule, i.e. Equations (17) and (18) equal to Equations (11) and (12), respectively.

**Proof:** Taking the global false alarm probability for example, we employ mathematical deduction to prove Proposition 1. For simplicity, denote $\alpha(K) = Q_{f,c}(K)$ and $\beta(K) = Q_{f,c}(K)$ as the two global false alarm probabilities with respect to $K$, and therefore when $K = 1$,

$$\alpha(K) = 1 - \sum_{i=1}^{N} \left( \frac{N}{1} \right) P_{f}^{i} (1 - P_{f})^{N-i}$$

$$= 1 - (1 - P_{f})^{N} = \beta(1) \quad (19)$$

Assuming $\alpha(K) = \beta(K)$ with $K = q$, then for $K = q + 1$, we have

$$\alpha(q) = \left( \begin{array}{c} N \\ q \end{array} \right) P_{f}^{q} (1 - P_{f})^{N-q} + \alpha(q + 1) \quad (20)$$

$$\beta(q) = \sum_{i=q}^{N} \left( \begin{array}{c} i-1 \\ q-1 \end{array} \right) P_{f}^{i} (1 - P_{f})^{i-q}$$

$$= P_{f}^{q} + \sum_{i=q+1}^{N} \left( \begin{array}{c} i \\ q \end{array} \right) \left( P_{f} - q \right) P_{f}^{i-q} (1 - P_{f})^{i-q}$$

$$+ \sum_{i=q+1}^{N} \left( \begin{array}{c} i-1 \\ q-1 \end{array} \right) P_{f}^{i-q} (1 - P_{f})^{i-q-1}$$

$$= \left( \begin{array}{c} N \\ q \end{array} \right) P_{f}^{q} (1 - P_{f})^{N-q} + \beta(q + 1) \quad (21)$$

From the above two expressions of the global false alarm probability, it is easy to derive $\alpha(k+1) = \beta(k+1)$. Therefore, it can be concluded that with any given integer $N$, Equation (17) equals to Equation (11) for every $K$ between 1 and $N$. Similarly, we also prove that Equation (17) equals to Equation (11).

## 5 | OPTIMISATION OF VCSS

In UAV-based interweave CR system, the final goal is to provide the UAV communication with spectrum resources by means of CR technology. Based on the previous detection performance of VCSS, we further investigate the throughput of UAV-based interweave CR system.

### 5.1 | Throughput of UAV-based interweave CR system

Let $P_{f}$ be transmission power of the UAV, $T_{0}$ be the throughput of UAV-based interweave CR system when it operates in the absence of the PU, and $T_{1}$ be the throughput when it operates in the presence of the PU. Then,

$$T_{0} = \log_{2} \left( 1 + \frac{P_{g}(k)^{2}}{\sigma_{0}^{2}} \right) \quad (22)$$

$$T_{1} = \log_{2} \left( 1 + \frac{P_{g}(k)^{2}}{\sigma_{0}^{2} (y + 1)} \right) \quad (23)$$

For a given frequency band of interest, we assume $P(H_{0})$ and $P(H_{1})$ to be the probability of the hypothesis $H_{0}$ and $H_{1}$, respectively. The UAV can transmit data in both cases. In the first case, the global decision declares the PU as idle when the PU is absent, there is no false alarm because the PU status is correctly sensed in mini-slots, the achievable throughput of UAV-based interweave CR system is $T_{d}T_{0}/T$. In the second case, the global decision declares the PU as idle when the PU is present, though the PU is present, the PU status is inaccurately declared as the idle status, the miss detection happens, the UAV may cause interference to the PU’s normal operation, the achievable throughput is $T_{d}T_{1}/T$. Define

$$T_{f} (K) = \frac{T_{d}}{T} T_{0} \left( 1 - Q_{f,c}(K) \right) P(H_{0}) \quad (24)$$

and

$$T_{d} (K) = \frac{T_{d}}{T} T_{1} \left( 1 - Q_{f,c}(K) \right) P(H_{1}) \quad (25)$$

Then, the average throughput for UAV-based interweave CR system is given by

$$T (K) = T_{f} (K) + T_{d} (K) \quad (26)$$

Because $T_{0} > T_{1}$, the first term in the RHS of Equation (25) dominates the achievable throughput; additionally, the achievable throughput of UAV-based interweave CR system in the second case may make the UAV abnormally transmit data because the PU network and the UAV communication will interfere with each other. Therefore, the optimisation problem can be approximated by

$$T (K) = T_{f} (K) \quad (27)$$

### 5.2 | Problem formulation

In TCSS or VCSS with the CDF rule, when SUs are allowed to access the idle channel, the data transmission duration is fixed.
Impact of various UAV characteristics

The optimisation of VCSS is to identify the optimal decision threshold $K$ for each frame such that the achievable throughput of UAV-based interweave CR system is maximised. Mathematically, the optimisation problem can be stated as follows:

$$
\max_K T(K) = \frac{\tau - A(K) \tau_s}{\tau} \cdot T_0 (1 - Q_{f,s}(K)) \cdot P(H_0) \quad (28)
$$

subject to $1 \leq K \leq N$  \hspace{1cm} (29)

5.3 Optimal decision fusion rule

From Equation (27), we can see the achievable throughput for UAV-based interweave CR system is a function with respect to the decision threshold $K$. In order to maximise the achievable throughput, we need to analyse $T(K)$ with respect to $K$ as follows.

Proposition 2. In a fixed frame duration $\tau = \hat{N} \tau_s$, where $\hat{N} > N$, there exists an optimal decision threshold $K$ that yields the maximum achievable throughput for UAV-based interweave CR system.

Proof: Taking derivative of $T(K)$ with respect to $K$, then

$$
\frac{\partial T(K)}{\partial K} = T(K + 1) - T(K)
$$

$$
= \frac{\tau - A(K + 1) \tau_s}{\tau} \cdot T_0 (1 - Q_{f,s}(K + 1)) \cdot P(H_0)
$$

$$
- \frac{\tau - A(K) \tau_s}{\tau} \cdot T_0 (1 - Q_{f,s}(K)) \cdot P(H_0) \quad (30)
$$

Then, we equivalently consider the following result:

$$
(\tau - A(K + 1) \tau_s) (1 - Q_{f,s}(K + 1))
$$

$$
- (\tau - A(K) \tau_s) (1 - Q_{f,s}(K))
$$

$$
= \hat{N} Q_{f,s}(K) - \hat{N} Q_{f,s}(K + 1) \tau_s
$$

$$
+ (A(K) (1 - Q_{f,s}(K))
$$

$$
- A(K + 1) (1 - Q_{f,s}(K + 1)) \tau_s \quad (31)
$$

According to the assumption $\hat{N} > N$, it is easily concluded that the above formula is greater than 0. In other words, $\frac{\partial T(K)}{\partial K} > 0$. That is to say, $T(K)$ is an increasing function with respect to $K$. Hence, there is a maximum point of $T(K)$ when $K = \hat{N}$.

It should be noted that though we prove the existence of the optimal detection threshold for the SZOF rule, no closed-form solution is available for the optimal $K$, and a search over all possible $K$ values is required. However, because $K$ is an integer and ranges from 1 to $N$, it is not computationally expensive to search for the optimal $K$ [31].

6 SIMULATION RESULTS

In this section, we compare our proposed SZOF rule with CDF rule to corroborate the performance superiority in VCSS through in-depth numerical simulations. In addition, we validate the correctness and effectiveness of our theoretical analyses on the available throughput for UAV-based interweave CR system. The values of important simulation parameters are shown in Table 1.

### TABLE 1 Simulation parameters

| Parameter       | Symbol | Value   |
|-----------------|--------|---------|
| Sensing frame   | $k$    | $10^3$  |
| Frame duration  | $\tau$ | 600 s   |
| Probability     | $P(H_0) / P(H_1)$ | 0.5     |
| Flight height   | $b$    | 200 m   |
| Sampling frequency | $f_s$  | 800 MHz |
| Number of mini-slots | $N$   | 20      |
| Sensing radian  | $\theta$ | $1/2\pi$ |
| Energy threshold| $\lambda$ | 1.008   |
| Noise standard variance | $\sigma_0$ | 1        |

6.1 Impact of various UAV characteristics on the performance

In order to build a fair comparison framework of the performance and throughput of VCSS with the CDF and SZOF rule, we assume that $K = \lceil N/2 \rceil$ in the $K$-out-of-$N$ rule. From Figures 5 and 6, we present the performance (including the global false alarm and detection probability, and the average number of decisions) of VCSS with the CDF and SZOF rule under various UAV characteristics (including the flight velocity, sensing radius, and SNR).

It is evident in Figures 5 and 6 that that the SZOF rule is able to provide with the same detection performance as the CDF rule under the same UAV characteristics. However, the faster the flight velocity or the smaller the sensing radius, the worse the detection performance. Apparently, the increasing velocity or the decreasing sensing radius make the sensing time shorten, resulting in the performance degradation. Furthermore, the SNR has no effect on the false alarm probability while it has a negative effect on the detection probability. In this regard, this can also be observed from the definition of the LSS performance.

Figure 7 plots the average number of decisions of VCSS with the CDF and SZOF rule. Unlike a fixed number of decisions $N$ in the CDF rule, the number of decisions required of the proposed SZOF rule is dynamic to make the global decision.
In details, the lower flight velocity, the higher sensing radius or SNR are beneficial to decrease the average number of decisions. This can be attributed to the fact that the lower flight velocity and the high sensing radius improve the detection performance and SNR improves the detection probability.

### 6.2 Impact of UAV characteristics on throughput

Following the previous parameter settings, we further observe the normalised throughput of VCSS with the CDF and SZOF rule and the impact of UAV characteristics on throughput. As shown in Figure 8, it seems that there is the optimal flight velocity maximising the throughput when SNR is −18 dB, but it is essentially an issue of the optimal sensing time, which has been extensively studied in [8]. According to our proposed VCSS model, because the sensing radius $\theta$ is a fixed value, the sensing time $\tau = \theta/\nu$ is related to the sensing radius $r$ and the flight velocity $\nu$. In other words, when the sensing radius and the flight velocity are appropriately set, there will be an optimal sensing time, otherwise the trade-off problem does not necessarily exist, such as when $r = 100$ m and $\gamma = −18$ dB, or $r = 800$ m and $\gamma$ varies from −18.4 dB to −18.8 dB. Hence, it can also be seen from Figure 9 that the sensing radius and the flight velocity have different effects on the throughput, but the SNR has no effect on the throughput. However, in contrast to the CDF rule, VCSS with the SZOF rule always provides a higher throughput regardless of UAV characteristics.
6.3 | Optimal SZOF rule

Now, in order to get a deep understanding about the optimisation of VCSS, simulation results are provided to verify the theoretical analysis and effectiveness of the proposed SZOF rule. We make comparisons between VCSS with the CDF and SZOF rule under various UAV characteristics, in terms of the performance and throughput.

Figures 10–12 illustrate the relationship between the throughput, the average number of decisions and the decision threshold \( K \). The throughput, as expected, always increases as \( K \) increases, then the maximal throughput is obtained when \( K = N \). Though

the throughput is jointly affected by the flight velocity and the sensing radius, it has nothing to do with SNR. More specifically, the average number of decision increase first and then decreases as \( K \) constantly increases, as shown in Figures 13–15. The reason for this phenomenon is that the faster the velocity or the larger the sensing radius, the faster the throughput growth in the early stage, and the slower the growth rate in the later stage.

In addition, the average number of decisions in the case of \( K = 1 \) and \( K = N \) approach to 2. Undoubtedly, when \( K = 1 \), the throughput is definitely lower than when \( K = N \). In addition, it is known that the detection performance increases as \( K \) increases. Therefore, the optimal decision rule is when \( K = N \), UAV-based interweave CR system can achieve the maximal throughput and best performance.
7 | CONCLUSION

With challenges of the UAV's spectrum demand and power limitation, an energy-efficient UAV-based interweave CR system is investigated. Unlike the participation of multiple SUs in TCSS, we propose a VCSS in the periodic spectrum sensing frame structure and an energy-efficient VCSS with SZOF rule to reduce the average number of decisions without any loss in the detection performance. Based on this rule, we further formulate the optimization problem of VCSS to obtain the highest throughput for UAV-based interweave CR system. Simulation results show that the correctness and effectiveness of our theoretical analyses, UAV-based interweave CR not only significantly reduces the number of decisions but also achieves the best detection performance and the maximal throughput when $K = N$.

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