UAV Based Optimized Virtual Cooperative Sensing Using Particle Swarm Optimization

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***Abstract*—Spectrum sensing utilizing unmanned aerial vehicles (UAVs) has become increasingly popular due to their advantageous line of sight (LoS) communication links. In traditional cognitive radio networks (CRNs), secondary users (SUs) opportunistically access the primary user (PU) channel through cooperative spectrum sensing, aiming to ensure reliable sensing while minimizing disturbances for licensed users. In this study, we evaluate an overlay mode of the CRN where a UAV acts as the SU. Instead of employing multiple SUs as in a terrestrial cooperative spectrum sensing setup with a fusion center (FC), our approach involves a single UAV performing virtual cooperative sensing by following a circular flight trajectory. During the UAV's sensing period, it consists of virtual mini-sensing slots akin to a group of SUs. The UAV enhances sensing reliability by performing local spectrum sensing within each mini-slot and combines the collected data using the voting scheme to make collective decisions. Moreover, the mini-slot sensing radian is optimized using particle swarm optimization (PSO) to readjust the sensing time. The optimized sensing time has resulted in increased throughput and reduce sensing time for the virtual cooperative sensing environments.**

***Index Terms*—Unmanned aerial vehicles, virtual cooperative sensing, particle swarm optimization, throughput, line of sight communication.**

I. Introduction

The versatility of unmanned aerial vehicles (UAVs) has recently captured the attention of various sectors, including commercial, public, and industrial applications. These UAVs have the potential to significantly improve communication systems by integrating wireless technologies and mobile networks, particularly in the upcoming sixth-generation (6G) future networks [1]. By utilizing UAVs in wireless communications, the speed and quality of communication can be enhanced while effectively reducing communication costs [2]. Additionally, the elevated altitude of UAVs offers improved line of sight (LoS) channels compared to terrestrial wireless communication channels, which often face challenges such as multipath fading, shadowing, and path loss [3].

Traditionally, UAVs operate within industrial scientific and medical (ISM) bands, IEEE-S bands, and IEEE-L bands, which are also utilized by other wireless technologies. Moreover, UAVs have been applied in various civilian unlicensed spectrum bands [4]. However, the proliferation of devices is expected to intensify the competition for available spectrum, leading to potential scarcity issues for UAVs shortly [5], [6]. To address this concern, integrating UAVs with cognitive radio (CR) technology enables dynamic spectrum access (DSA) and opportunistic spectrum access based on application requirements, thereby relieving spectrum congestion. Additionally, a UAV-CR network can contribute to reduced energy consumption, transmission delays, and overlaid deployment [5].

The use of UAVs in a cognitive radio network (CRN) is discussed in [7]. The UAV is an energy-harvested CR node in this setup, overseeing spectrum sensing and transmitting data using the available primary user (PU) spectrum. UAVs are equipped with batteries that power both their mobility and communication capabilities. To address the power control complexity, [4] proposes power solutions that are more efficient than existing numerical approaches.

In [8], the authors address the dynamic cooperative spectrum sensing (CSS) and channel access problem within a clustered UAV network. Unlike previous studies that focused on reinforcement learning (RL) approaches for single secondary user (SU) scenarios, where the user's reward only considered idle spectrum utilization, [8] formulates the challenge as a multi-agent RL (MARL) problem.

Despite the numerous advantages of UAV-CR networks, limitations such as reporting delay, control channel bandwidth, and high-cost overhead hinder the cooperative gain. Additionally, due to energy constraints imposed by limited battery power, energy efficiency becomes a critical concern for CSS in UAV-CR systems. It is essential to recognize the impact of average decisions on CSS performance while optimizing throughput in the UAV-CR system, as emphasized in [9], [10]. Enhancing the sensing performance of CSS can effectively increase spectral efficiency by maximizing secondary link throughput [11]. However, a longer sensing time decreases the data transmission rate, reducing network throughput. Hence, it is crucial to optimize the sensing time compared to existing schemes carefully [9], [11], [12] to maximize the throughput of the secondary links. In contrast to previous studies that assume fixed sensing and data transmission times, this research focuses on reconfiguring the sensing time in a UAV-CR interweave network, where the UAV serves as the SU. Instead of involving multiple SUs in traditional CSS, a virtual cooperative model based on a periodic sensing frame structure is introduced, incorporating a particle swarm optimization (PSO) solution.

This research addresses concerns about energy efficiency and throughput in UAV-based CR networks. The following are some of the notable contributions of this work:

- The paper investigates a UAV-based CR network, where a UAV serves as a SU to perform cooperative spectrum sensing virtually. Unlike traditional CSS approaches, where many SUs individually sense the PU channel and report their decisions to a fusion center (FC) for the final decision, a virtual cooperative method is proposed that divides the sensing time into many small sensing time slots and combines the decisions made in these slots for collective decision.
- This work focuses on optimizing the sensing time through adjustment of the mini-slot sensing radian for the virtual cooperative scheme using the PSO technique. This optimization contributes to an increase in the normalized throughput of the networks.
- The study explores the efficacy of the optimized sensing time within the virtual cooperative sensing environments to minimize the number of decisions made and reduce the consumption of extensive communication resources.

The paper is structured into the following sections. Section II presents the system model, outlining the critical components of the study. In Section III, the virtual cooperative sensing approach is discussed. The utilization of PSO for sensing time identification, performance metric evaluation, and throughput analysis is presented in Section IV. Simulation results are demonstrated in Section V. Finally, Section VI provides the concluding remarks of the paper.

II. System Model

A. UAV trajectory and frame structure

In this study, a UAV is employed as a spectrum sensor for the PU spectrum within the interweave mode of the CRN. Figure 1 illustrates the scenario, with the PU at the center and the UAV following a circular trajectory path. The UAV detects the PU signal within a 3D ring space and accesses the vacant spectral band when it is detected as unoccupied.

The objective is to enhance the throughput of UAV-based cooperative spectrum sensing (CSS) for a specific fusion rule. The research primarily focuses on the data transmission time within the frame structure, along with the spectrum sensing time. Figure 2 illustrates that increasing the mini-slot sensing time (τ_s) leads to a decrease in the data transmission time (τ_d), as a longer sensing time reduces the opportunities for the UAV to transmit data within τ_d. Furthermore, figure 3 depicts the UAV's circular flight trajectory around the PU [13], assuming a flight radius (r) and a flight altitude (h), where the sensing distance is also represented

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

where $R_p \leq s \leq R_s$.

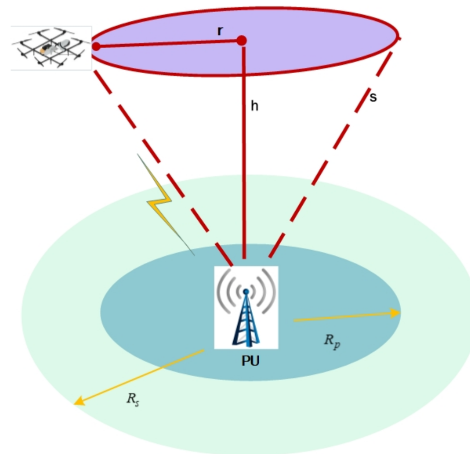

Fig. 1. UAV-based spectrum sensing model.

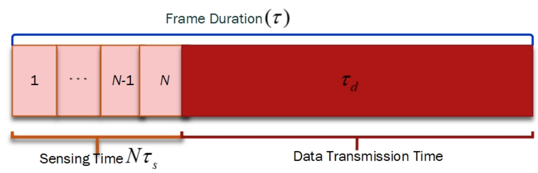

Fig. 2. Frame structure with virtual sensing and data transmission time.

In UAV-based CR networks, the UAV performs spectrum sensing to detect the availability of the PU spectrum, utilizing it when it is deemed free from PU activity. Unlike ground-based spectrum sensing, the communication channel between the UAV-based CR and the ground-based PU is characterized as Line-of-Sight (LoS), resulting in reduced fading effects compared to ground communication.

B. Virtual cooperative sensing scheme

In contrast to traditional CSS approaches that involve multi-user cooperation for achieving high detection performance, this work focuses on a scenario where a single UAV performs spectrum sensing. To enhance the detection performance, the proposed approach introduces collaboration in multiple mini-slots. In this method, the UAV senses the PU channel at different locations along its flight path, improving the overall detection performance. This approach is referred to as virtual cooperative sensing.

The flight path is illustrated as a two-dimensional (2D) plane in figure 3, utilizing a radius of r for clearer representation. The virtual cooperative sensing model's periodic spectrum sensing frame structure divides the flight track into 'N' sensing radians, each with a duration denoted as 'θ,' while 'φ' represents the data transmission radian. Assuming a uniform UAV flight velocity 'v' and radius 'r,' the sensing duration of the i^{th}' mini-slot can be expressed as $\tau_{s,i} = \frac{\theta r}{v}$. For a given fixed value of UAV flight velocity (v) and radius (r), the reconfiguration of the sensing duration (θ) results in the effective sensing time (τ_s). Likewise, the duration of data transmission $\tau_d = \frac{\varphi r}{v}$.

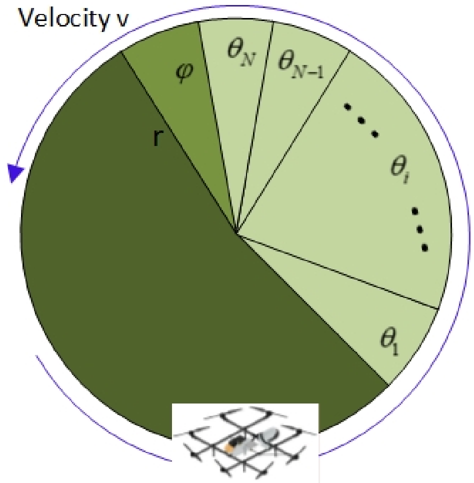

Fig. 3. Flight model of UAV.

In the given setting, a UAV performs spectrum sensing independently at multiple sensing locations. It then combines the collected data to enhance cooperative outcomes. This method improves detection performance and eliminates the need for resource allocation among SUs when the PU is not accessible.

C. Mini-slots local spectrum sensing

A virtual cooperative setting is created by employing local spectrum sensing in each mini-slot duration. Multiple detection schemes are available, such as the energy detector, matched filter, wavelet detector, and cyclo-stationary detectors. Among these options, the energy detector is commonly favored due to its simplicity of implementation and no need for prior knowledge about the PU channel. Therefore, the proposed local sensing model represents the presence and absence states of the PU in the i^{th} mini-slot, as explained in the reference [14].

$$y_i(m) = \begin{cases} u_i(m) & : H_0 \\ g(k)s_i(m) + u_i(m) & : H_1 \end{cases}, \tag{2}$$

The proposed model uses H_0 to represent the absence hypothesis of the primary user (PU) signal, while H_1 denotes the presence hypothesis. Within the i^{th} mini-slot, the PU signal received by the UAV is represented as $s_i(m)$, which experiences distortion due to the channel gain $g(k)$ corresponding to the k^{th} frame. The complex Gaussian noise is denoted as $u_i(m)$ and is assumed to be statistically independent of $s_i(m)$, as mentioned in reference [15].

In the context of the UAV receiver being positioned at a distance 's' from the PU transmitter, the signal propagates through free space to reach the UAV. The channel model in this scenario assumes Line-of-Sight communication, where the signal travels along a circular flight path without encountering obstacles between the PU transmitter and UAV receiver, as described in reference [16]. The channel gain is denoted by $g(k) = \frac{\xi}{s}$, where ξ is determined by $\xi = \frac{c}{4\pi f_s}$, with 'c' representing the speed of light and f_s denoting the sampling frequency, as explained in reference [17].

The received signal energy captured by the UAV can be mathematically expressed as follows

$$E_i(y) = \sum_{m=1}^{M} |y_i(m)|^2. \tag{3}$$

The central limit theorem indicates that for a sufficiently large M, the expression for $E_i(y)$ can be approximated as

$$E_i(y) \sim \begin{cases} N\left(\mu_0,\ \sigma_0^2\right) & : H_0 \\ N\left(\mu_1,\ \sigma_1^2\right) & : H_1 \end{cases}, \tag{4}$$

where $\mu_0 = M\sigma_0^2$ and $\sigma_0^2 = 2M\sigma_0^4$ are the mean and variance under H_0 hypothesis, while $\mu_1 = M(\gamma+1)\sigma_0^2$, and $\sigma_1^2 = 2M(\gamma+1)^2\sigma_0^4$ are the mean and variance with H_1. $\gamma = |g(k)|^2\sigma_1^2/\sigma_0^2$ is the PU average signal-to-noise ratio (SNR) at the mini-slot of interest.

The energies of local spectrum sensing in the mini-slots are compared to a decision threshold λ to determine the probabilities of local detection and false detection, as outlined in [18]

$$\begin{aligned} P_f &= P(E_i(y) > \lambda \,|H_0\,) \\ &= Q\left(\left(\frac{\lambda}{\sigma_0^2} - 1\right)\sqrt{\frac{r\theta_{s,i}f_s}{v}}\right), \end{aligned} \tag{5}$$

$$\begin{aligned} P_d &= P(E_i(y) > \lambda \,|H_1\,) \\ &= Q\left(\left(\frac{\lambda}{\sigma_0^2(\gamma+1)} - 1\right)\sqrt{\frac{r\theta_{s,i}f_s}{v}}\right). \end{aligned} \tag{6}$$

The expression uses the standard Gaussian complementary distribution function, denoted as $Q(\cdot)$.

III. Combine decision of the virtual cooperative sensing scheme

In a typical cooperative spectrum sensing (CSS) setup, the fusion center (FC) collects the sensing results from multiple secondary users (SUs) to make a global decision regarding the availability of the spectrum. In the case of the "$K-in-N$" fusion rule, if a minimum of K out of N user decisions indicate that the PU channel is occupied, the FC broadcasts and communicates the channel as active [19].

The interweave cognitive radio system in this work has replaced conventional multi-user cooperative sensing with single-user mini-slot cooperative sensing. In this approach, the UAV performs local spectrum sensing in each mini-slot and generates a final binary decision using the K-out-of-N rule within the sensing slot, as discussed in reference [20].

The global decision $F(k)$ based on the K-out-of-N rule, can be expressed as

$$F(k) = \begin{cases} \sum_{i=1}^{N} r_i \geq K & : H_1 \\ \sum_{i=1}^{N} r_i < K & : H_0 \end{cases}. \tag{7}$$

In this context, r_i represents the local decision made in the i^{th} mini-slot. The technique utilizes virtual mini-sensing slots to leverage the diversity of virtual sensing, thereby mitigating the sensitivity of individual sensing slots and enhancing detection performance. Consequently, it helps alleviate the demand for a powerful FC and concentrates the sensing cost within an Unmanned Aerial Vehicle-CRN [20]. In this discussion, we present the $K-in-N$ rule as a low-complexity approach that doesn't necessitate extensive prior information about the primary user signal.

By leveraging virtual cooperative sensing, detection performance can be enhanced; however, this improvement comes at the expense of increased control channel overhead, reporting delay, and higher energy consumption. These factors limit the achievable cooperative gain. Considering the limited battery power of UAVs, energy efficiency becomes a crucial aspect that needs to be considered when implementing virtual cooperative sensing for UAVs. Specifically, the global detection probabilities (C_d^c) and false alarm probabilities (C_f^c) associated with virtual cooperative sensing based on the $K-in-N$ rule are as follows

$$C_f^c = \sum_{i=K}^{N} \binom{N}{i} P_f^i (1-P_f)^{N-i}, \tag{8}$$

$$C_d^c = \sum_{i=K}^{N} \binom{N}{i} P_d^i (1-P_d)^{N-i}. \tag{9}$$

A. UAV-CR network throughput

The throughput of the UAV, denoted as T_0, in the absence of the primary user (PU), and the throughput of the UAV, represented as T_1, in the presence of the PU, can be expressed as follows

$$T_0 = \log_2\left(1 + \frac{g(k)^2 P_t}{\sigma_0^2}\right), \tag{10}$$

$$T_1 = \log_2\left(1 + \frac{g(k)^2 P_t}{(\gamma+1)\sigma_0^2}\right). \tag{11}$$

Here, γ represents the average signal-to-noise ratio from the primary user to the unmanned aerial vehicle. In the case of H_0, there are no false alarms, and the achievable throughput of the UAV-CR system is given by $\tau_d T_0/\tau$. On the other hand, under the H_1 hypothesis, where the cooperative decision fails to detect the presence of the PU, resulting in a miss-detection, the UAV's achievable throughput is defined as $\tau_d T_1/\tau$. Therefore, the overall relationship can be expressed as follows

$$T_f(K) = \frac{\tau_d}{\tau} T_0 \left(1 - C_f^s(K)\right) P(H_0), \tag{12}$$

and

$$T_d(K) = \frac{\tau_d}{\tau} T_1 \left(1 - C_d^s(K)\right) P(H_1). \tag{13}$$

Then, the average throughput is given by

$$T(K) = T_f(K) + T_d(K). \tag{14}$$

Within the given equation, the term $T_f(K)$ holds greater significance compared to $T_d(K)$ due to the relationship $T_0 > T_1$. Consequently, we can approximate $T(K)$ as follows

$$T(K) = T_f(K). \tag{15}$$

In the context of virtual cooperative sensing the data transmission time $\tau_d = \tau - N\tau_s$ remains constant when the secondary users are permitted to access the available channel. Subsequently, this predefined data transmission time is readjusted, and the optimal sensing time τ_s is determined using the particle swarm optimization technique in the subsequent section. The mathematical formulation of the throughput optimization problem is presented as follows

$$\max_{\theta_s} T(\theta_{s,i}) = \left(1 - \frac{Nr\theta_{s,i}}{\tau v}\right) T_0 \left(1 - C_f^c\right) P(H_0), \tag{16}$$

where $1 \leq K \leq N$.

IV. Optimal sensing radian using particle swarm optimization

The paper introduces a PSO algorithm that utilizes a fixed number of particles, where each particle is represented as a vector with a single element. These elements are initialized randomly and enter an iterative process. During each iteration, the performance of each particle is evaluated based on its proximity to the objective function, which involves substituting the particle into the objective function. Furthermore, the best-performing particle is identified after each iteration. Figure 2 depicts the flowchart of the proposed PSO-based scheme. The step-by-step procedure for the method is as follows.

A. Step 1: Population initialization

The algorithm is initialized with an initial population of randomly generated, N, particles as follows

$$\overrightarrow{\theta_x} = [\theta_i], i \in 1, 2, ..., N. \tag{17}$$

The fitness of each PSO particle is evaluated based on its throughput results, denoted as $T(\vec{\theta}_1),, T(\vec{\theta}_2),, ...,, T(\vec{\theta}_N)$. Consequently, the particle with the highest throughput is identified as the global best.

B. Population update

The global best position θ^g represents the particle with the highest throughput among all particles in θ^x, as determined by the throughput equation. In the PSO, each particle has the potential to update itself if its new version proves superior to the previous one. The local best particles within the population are chosen as $\theta^P = \theta^x$, serving as reference points for individual particle improvement.

Initially, both the positions and velocities of the particles are initialized to zero. The updating of particle velocities occurs through the utilization of individual and collective intelligence

$$\begin{aligned} V_{(i+1)j} &= V_{ij} + C_1 \times R_1 \times \left(\theta_{ij}^P - \theta_{ij}^x\right) \\ &+ C_2 \times R_2 \times \left(\theta_j^g - \theta_{ij}^x\right). \end{aligned} \tag{18}$$

The updating of particle velocities involves the incorporation of learning acceleration coefficients, represented by C_1 and C_2, which respectively govern the particles' individual and social contributions. Additionally, the process includes introducing a stochastic element to the algorithm by using uniformly distributed random numbers, R_1 and R_2, ranging from 0 to 1.

After computing the particles' velocities with the local and global intelligence, the velocities are then bounded by rounding them to their respective extremes

$$V_{(i+1)j} = \begin{cases} \max(V), & V_{ij} > \max(V) \\ \min(V), & V_{ij} \leq \max(V) \end{cases}. \tag{19}$$

Subsequently, the particle's position is updated as follows

$$\theta^x_{(i+1)j} = \theta^x_{ij} + V_{(i+1)j}. \tag{20}$$

In this context, $E_{(i+1)j}$ represents the updated population.

C. Modification to local and global best

The local best particles are examined for any potential modifications as follows

$$\theta^P_i = \begin{cases} \theta^x_i, f(\theta^x_i) < f(\theta^P_i) \\ \theta^P_i, \text{otherwise} \end{cases}. \tag{21}$$

In this case, the fitness function denoted by $f(.)$ serves as the selection criteria in equation (12). The fitness of θ^P_i in equation (16) is then compared with θ^g to identify any potential improvements as follows

$$\theta^g = \begin{cases} \theta^P_i, f(\theta^P_i) < f(\theta^g) \\ \theta^g, \text{otherwise} \end{cases}, i = 1, ..., N_0. \tag{22}$$

V. Numerical Results and Discussions

Simulations consist of rotating UAVs in the air that try to sense the occupancy of the PU channel. The results show a performance comparison of the simple virtual cooperative spectrum sensing (VCSS) with the proposed particle swarm optimization (PSO) based VCSS (PSO-VCSS) scheme. The $P(H_0)$ and $P(H_1)$ hypotheses probabilities are 0.5 for a frame duration (τ) of 600s. The UAV is assumed to rotate at a height of 200m. A total of 20 mini slots are considered with an energy threshold of λ equal to 1.008. UAV rotation velocity changes in the range of 5m/s 25m/s at the radius of 100m 300m. Similarly, the SNRs in dB are adjusted in the range of -20(dB) -10(dB). Normalized throughput and sensing time results are collected for comparison for the simple VCSS and proposed PSO-VCSS in the following sections.

A. Case 1: Performance against the changing flight velocity

Figures 4 and 5 compared the simple VCSS and proposed VCSS against the increasing UAV flight velocities. The result shows a rise in the throughput results as the UAV velocity increase from 5m/s to 25m/s in figure 4, while the sensing time decreases for both the simple VCSS and proposed VCSS. A slight increase is observed as the SNRs are changed from -20dB to -16dB in figure 4; however, the sensing time of VCSS remains unchanged for the simple VCSS. The proposed scheme presented higher throughput performance with minimum sensing time at $SNRs_1$ and $SNRs_2$.

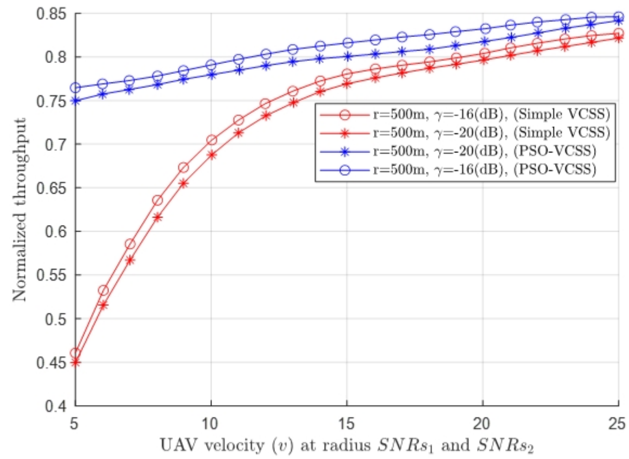

Fig. 4. Throughput vs. velocity.

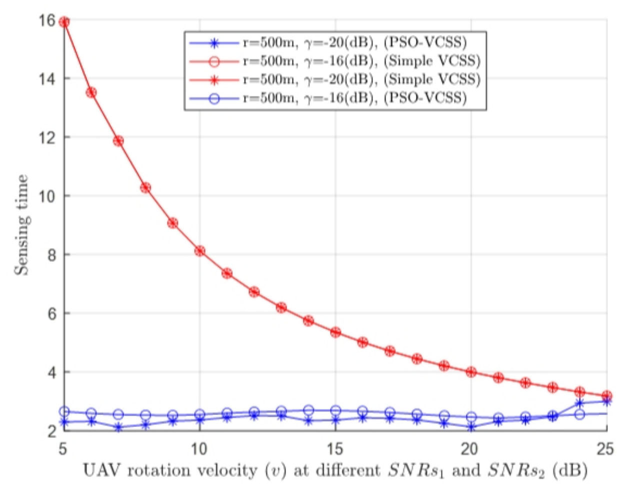

Fig. 5. Sensing time vs. velocity.

B. Case 2: Performance against increasing SNRs

In case 2, the UAV flight radius is kept at 500m at the SNRs of -18dB. The throughput and sensing time are investigated at two flight velocities, v_1=17m/s, and v_2=22m/s, as shown in figures 6 and 7. The findings in case 2 show that increasing SNRs leads to a higher increase in the network throughput for the proposed PSO-VCSS compared to the simple VCSS. The sensing time of the simple VCSS remains constant when the SNRs are changed from -20dB to -10dB, while the proposed PSO-VCSS has performed a similar job with a reduced sensing time.

VI. Conclusions

Traditional CSS schemes engage more than one SUs to perform spectrum sensing and report their local decisions to

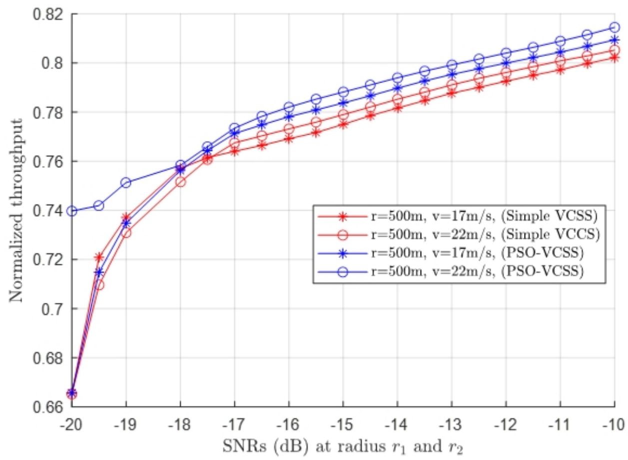

Fig. 6. Throughput vs. SNRs (dB).

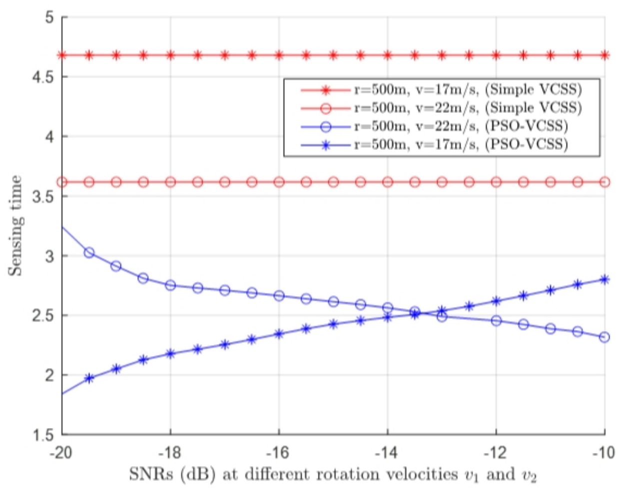

Fig. 7. Sensing time vs. SNRs (dB).

the FC for a final decision. This work employs flying UAVs in the CR network, which work as multiple SUs virtually to perform spectrum sensing. The sensing angle of the UAV is divided into mini-slots, where the local spectrum sensing is performed and combined for a final decision. The LoS propagation of the UAV-based interweave CR system can perform spectrum sensing jobs more accurately than in the case of multiple SUs on the ground. For further enhancement, the sensing time for the VCSS schemes is optimized using particle swarm optimization, leading to a better sensing performance. Throughput and sensing time investigations show improved performance for the PSO-VCSS scheme compared with the simple VCSS scheme.

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