Spatio-Temporal Fusion for Small-scale Primary Detection in Cognitive Radio Networks

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***Abstract*—In cognitive radio networks (CRNs), detecting small-scale primary devices—such as wireless microphones (WMs)—is a challenging, but very important, problem that has not yet been addressed well. We identify the data-fusion range as a key factor that enables effective cooperative sensing for detection of small-scale primary devices. In particular, we derive a closed-form expression for the optimal data-fusion range that minimizes the average detection delay. We also observe that the sensing performance is sensitive to the accuracy in estimating the primary's location and transmit-power. Based on these observations, we propose an efficient sensing framework, called `DeLOC`, that iteratively performs location/transmit-power estimation and dynamic sensor selection for cooperative sensing. Our extensive simulation results in a realistic CRN environment show that `DeLOC` achieves near-optimal detection performance, while meeting the detection requirements specified in the IEEE 802.22 standard draft.**

I. Introduction

Cognitive radio networks (CRNs) have recently been recognized as an attractive means to mitigate the spectrum-scarcity problem that is expected to occur due to the rapidly growing wireless services and user population. In CRNs, unlicensed (secondary) devices can opportunistically access temporarily available licensed spectrum bands, i.e., spectrum bands unoccupied by the primary users. Among the numerous challenges that CR technology faces for its successful realization, spectrum sensing, as the key enabling technology, has been studied extensively.

While most of the previous research on spectrum sensing has focused on various aspects of detecting *large-scale* primary signals (e.g., TV signals) [1]–[4], detection of small-scale primary devices, such as WMs, still remains to be a difficult, open problem for the following reasons. First, while a TV signal has a large transmission range (up to 150 km), the WM signal has a small spatial footprint. The transmission range of a WM is 100-150 m due to its weak transmit power (typically 10-50 mW) [5]. As a result, the 802.22 needs a separate dense sensor network for WM detection [6], or more preferably, an efficient cooperative sensing mechanism tailored to WM detection, which is the main focus of this paper.

Second, the ON-OFF patterns of WMs have high spatial and temporal variations [7]. WMs can be turned on at any location and at any time without prior notification to secondary users. They are usually mobile and used for short periods of time. Therefore, it is practically infeasible to maintain a database for WMs [8] or profile all the possible locations and schedules of WM usage in real time. More importantly, this unpredictability makes it hard for the BS to select sensors for cooperative sensing.

The work described in this paper was supported in part by the NSF under Grant CNS-0721529.

Third, despite its small footprint, a WM must be detected according to the strict sensitivity requirement imposed by the FCC. For example, the 802.22 standard draft specifies that sensors must be able to detect as weak WM signals as -107 dBm over a 200 KHz band within 2 seconds with both false-alarm and mis-detection probabilities less than 0.1. However, a recent measurement study [9] indicates that sensors suffer from a high false-alarm rate when detecting WM signals due to their weak signal strengths [10]. Therefore, there is an urgent need for devising robust sensing mechanisms that meet the strict detection requirements of small-scale primaries, while minimizing the sensing overhead and detection delay.

Despite its practical importance, however, little has been done for the detection of small-scale primary signals. To the best of our knowledge, the disabling beacon protocol, recently proposed by the 802.22 Task Group 1 (TG 1) [11], [12], is the only known solution. The disabling beacon protocol aims to enhance WM detection by transmitting a specially-designed signal before starting the WM devices. It is suitable for carrying additional information, such as the signature/authentication and geo-location of WMs, which helps improve spectrum efficiency via better spatial [6], [13] and frequency [14] reuse. However, the beacon protocol still has the following limitations. First, we do not expect that all WM users will be equipped with a separate beacon device in the near future considering the fact that most users have not even registered their WMs. Second, the transmit power of the beacon message is limited to the same level as the WM's (i.e., 250 mW in UHF band), and thus, beacons cannot compensate for the low sensor density in 802.22 [11]. Lastly, the beacon protocol incurs a significant sensing-time overhead (i.e., 5-100 ms) [11] compared to the simple energy detection.

Motivated by these practical needs, we propose an efficient sensing framework for *small-scale* primary detection using cooperative sensing. We first assume that the WM's location and transmit-power are available to the secondary users, and derive the optimal fusion-range within which the sensors cooperate to minimize the detection delay, i.e., the number of sensing rounds needed for detecting a primary. Based on our analytical findings, we then design a practical framework, called `DeLOC`, which performs joint cooperative sensing and location/power estimation, in order to meet the detectability requirements, while minimizing the detection delay.

II. PRELIMINARIES

In this section, we introduce the network model, the WM sensing model, and the wireless signal-propagation model.

A. Network Model

We consider a CRN consisting of primary and secondary users in the same geographical area. While the techniques that we propose can be applied to other small-scale primary transmitters, without loss of generality, we will focus on WM detection in IEEE 802.22 WRANs. WMs use a weak transmit power around 10-50 mW, or below [5], [13], and its transmission range is only 150-200 m, which is much smaller than the typical 802.22 cell radius of 33 km. We assume secondary users (called CPEs) have been deployed in an area A, i.e., an IEEE 802.22 WRAN cell, following a point Poisson process with density ρ, i.e., $n_A \sim Poi(n;\rho|A|)$. Such CPEs are stationary and their locations are known to the BS. We assume a low sensor density ρ as the typical density of CPEs (i.e., households) in rural areas is very low (around $1.25/\text{km}^2$) [15].

B. WM Sensing Model

We make the following assumptions regarding the WM signal detection: Sensors

A1) use the energy detection for PHY-layer sensing, and
A2) sense an entire 6 MHz-wide TV channel.

Regarding A1, the feature detection cannot be applied for WM detection because, unlike the TV signals, there is no standard modulation specified by the FCC R&O for WM signals [16]. The test statistic of the energy detector is an estimate of average received signal strength (RSS) including the noise power. It can be approximated as Gaussian using the Central Limit Theorem (CLT) as in [17]:

$$T_n \sim \begin{cases} \mathcal{N}\big(N_o, \frac{N_o^2}{M_s}\big) & \mathcal{H}_0 \text{ (no primary signal)} \\ \mathcal{N}\big(P_n + N_o, \frac{(P_n+N_o)^2}{M_s}\big) & \mathcal{H}_1 \text{ (primary signal exists)}, \end{cases} \quad (1)$$

where P_n is the power of a received primary signal at sensor n, N_o the noise power, i.e., -95.2 dBm for a TV channel with 6 MHz bandwidth [18], and M_s the number of signal samples, e.g., 6×10^3/ms for 6 MHz TV band at the Nyquist rate.

Regarding A2, WMs use a relatively narrow frequency band, i.e., 200 KHz, compared to a 6 MHz TV band. Therefore, sensing the entire TV channel simplifies the sensing design at the cost of decreased measured signal-to-noise ratio (SNR) due to the increased noise level over a 6 MHz-wide channel.

C. Signal-Propagation Model

We assume that sensor n's received primary signal strength can be characterized by the following propagation model:

$$P_n = P_o \Big(\frac{d_o}{d_n}\Big)^{\alpha} e^{X_n} e^{Y_n} \quad \text{(Watt)}, \quad (2)$$

where P_o is the transmission power of the primary transmitter, α the path-loss exponent, d_o the reference distance (e.g., 1 m), and d_n the distance from the primary transmitter to sensor n. Shadow fading and multi-path fading are accounted for in e^{X_n} and e^{Y_n}, respectively, where $X_n \sim \mathcal{N}(0,\sigma^2)$ $\forall n$. The log-normal shadow fading is often characterized by its dB-spread, σ_{dB}, which has the relationship $\sigma = 0.1\ln(10)\sigma_{dB}$.

III. DETECTION OF SMALL-SCALE PRIMARY VIA SPATIO-TEMPORAL DATA-FUSION

In this section, we first formulate the small-scale primary detection problem as a sequential hypothesis testing problem. We then derive the optimal data-fusion range that minimizes the average detection delay.

A. Hypothesis Testing

Let $\theta_t = [T_1, \ldots, T_{|S_t|}]^T$ denote the vector of test statistics (i.e., RSSs) measured at the sensing stage t by a set S_t of cooperating sensors. A sensor is selected by the BS if it is within the fusion range R_f from the WM transmitter. The fusion range, and hence the set of cooperating sensors, can differ in each sensing stage according to the WM's estimated location and transmit-power level. Let $\theta = [\theta_1^T, \ldots, \theta_N^T]^T$ denote the $M \times 1$ vector of test statistics measured at sensors over N sensing stages, where $M = \sum_{t=1}^N |S_t|$.

Our detection problem is then a binary Gaussian classification problem where the observed test statistic θ belongs to one of two classes, $\mathcal{H}_0$ or $\mathcal{H}_1$, where:

$$\begin{aligned} &\mathcal{H}_0 : \theta \sim \mathcal{N}(\mu_0 \times \mathbf{1}, \Sigma_0) \quad \text{(no primary signal)} \\ &\mathcal{H}_1 : \theta \sim \mathcal{N}(\mu_1 \times \mathbf{1}, \Sigma_1) \quad \text{(primary signal exists)}, \end{aligned}$$

where μ_k and Σ_k are the mean vector and covariance matrix of the test statistics under $\mathcal{H}_k, k \in \{0,1\}$. The average test statistics under each hypothesis are $\mu_0 = N_o$ and $\mu_1 = P_R + N_o$, where N_o and P_R are the average noise power and received primary signal power at sensors, respectively.[1]

B. Sensing Scheduling via SPRT

In `DeLOC`, the BS schedules the sensing periods (stages) until it obtains a sufficient amount of information for making a final decision. We adopt Wald's *Sequential Probability Ratio Test* (SPRT) [19] to process the statistics and determine when to stop sensing. SPRT is optimal in the sense of minimizing the average number of observations, given bounded false-alarm probability Q_{FA} and mis-detection probability Q_{MD}.

With SPRT, a decision is made based on the observed sequence of test statistics, $\{\theta_t\}_{t=1}^N$, using the following rules:

$$\begin{aligned} \Lambda_N \geq B &\Rightarrow \text{ accept } \mathcal{H}_1 \text{ (primary signal exists)} \\ \Lambda_N < A &\Rightarrow \text{ accept } \mathcal{H}_0 \text{ (no primary signal)} \\ A \leq \Lambda_N < B &\Rightarrow \text{ take another observation}, \end{aligned}$$

where A and B $(0 < A < B < \infty)$ are the detection thresholds that depend on the desired values of Q_{FA} and Q_{MD}. The decision statistic Λ_N is the log-likelihood ratio derived from a sequence of test statistics $\theta_1, \ldots, \theta_N$ as follows:

$$\Lambda_N \triangleq \lambda(\theta_1, \ldots, \theta_N) = \ln \frac{f_1(\theta_1, \ldots, \theta_N)}{f_0(\theta_1, \ldots, \theta_N)}, \quad (3)$$

where $f_k(\theta_1, \ldots, \theta_N)$ is the joint p.d.f. of the sequence of test statistics (i.e., measured RSSs) under the hypothesis $\mathcal{H}_k$ $\forall k \in \{0,1\}$.

Recall that $\{\theta_t\}_{t=1}^N$ are Gaussian, and assuming they are i.i.d., Eq. (3) becomes:

$$\Lambda_N = \sum_{t=1}^N \lambda_t = \sum_{t=1}^N \ln \frac{f_1(\theta_t)}{f_0(\theta_t)} = \sum_{t=1}^N \sum_{n=1}^{|S_t|} \ln \frac{f_1(T_n)}{f_0(T_n)}, \quad (4)$$

[1] Since the BS does not have the exact distribution of the received primary signal strengths, the BS can set P_R to -107 dBm, which is the detectability requirement in 802.22 [11].

where the test statistic can be approximated as Gaussian using the Central Limit Theorem (CLT) as $T_n \sim \mathcal{N}(\mu_k, \sigma_n^2)$ under $\mathcal{H}_k$, as shown in Eq. (1).

We now consider the *normalized* test statistics (i.e., RSSs) to simplify the derivation of the average number of sensing rounds. Let $t_n \triangleq T_n \cdot \sigma_n^{-1}$ denote the normalized test statistic, i.e., $t_{n|\mathcal{H}_k} \sim \mathcal{N}(\phi_k, 1)$ where $\phi_k = \frac{\mu_k}{\sigma_n}$, $\forall k$. Then, we have:

$$\lambda_t = \sum_{n=1}^{|S_t|} \ln \frac{h_1(t_n)}{h_0(t_n)} = (\phi_1 - \phi_0) \sum_{n=1}^{|S_t|} t_n + \frac{1}{2} \sum_{n=1}^{|S_t|} (\phi_0^2 - \phi_1^2), \quad (5)$$

where $h_k(\cdot)$ is the p.d.f. of $t_{n|\mathcal{H}_k}$.

Based on Eqs. (4) and (5), the decision statistic Λ_N can be expressed as:

$$\begin{aligned}\Lambda_N &= (\phi_1 - \phi_0) \sum_{t=1}^{N} \sum_{n=1}^{|S_t|} t_n + \frac{1}{2} \sum_{t=1}^{N} \sum_{n=1}^{|S_t|} (\phi_0^2 - \phi_1^2) \\ &= (\phi_1 - \phi_0) \sum_{n=1}^{M} t_n + \frac{M}{2} (\phi_0^2 - \phi_1^2), \end{aligned} \quad (6)$$

where $M = \sum_{t=1}^{N} |S_t|$ is the total number of test statistics collected by the BS through N sensing stages.

C. Minimization of the Average Detection Delay

Recall that our goal is to minimize the number of sensing rounds that the BS has to schedule to meet the desired detection performance requirements, e.g., $Q_{FA}, Q_{MD} \le 0.01$. Thus, we first derive a closed-form expression for the average number of sensing rounds required until a decision is made (i.e., either boundary A or B is reached).

The average number of sensing rounds required for making a decision (denoted by $\mathbb{E}[N]$) can be computed as [19]:

$$\mathbb{E}[N] = \mathbb{E}[\lambda \,|\, \mathcal{H}_k]^{-1} \times \mathbb{E}[\Lambda_N], \quad (7)$$

which we discuss next.

First, using Eq. (5), the average value of the log-likelihood ratio λ under hypothesis $\mathcal{H}_k$ can be derived as:

$$\mathbb{E}[\lambda \,|\, \mathcal{H}_k] = (\phi_1 - \phi_0)\, \mathbb{E}\left[\sum_{n=1}^{|S_t|} t_{n|\mathcal{H}_k}\right] + \frac{1}{2} \mathbb{E}\left[\sum_{n=1}^{|S_t|} (\phi_0^2 - \phi_1^2)\right]. \quad (8)$$

Next, the expectation of Λ_N in Eq. (7) can be found as follows. Suppose $\mathcal{H}_1$ holds, then Λ_N will reach the decision boundary A with the desired mis-detection probability b^*; otherwise, it will reach B. Thus, according to [19]:

$$\mathbb{E}[\Lambda_N \,|\, \mathcal{H}_1] = b^* \ln \frac{b^*}{1 - a^*} + (1 - b^*) \ln \frac{1 - b^*}{a^*}. \quad (9)$$

Based on Eqs. (7), (8) and (9), we can derive the average number of sensing rounds needed for decision-making as:

$$\mathbb{E}[N \,|\, \mathcal{H}_1] = \frac{b^* \ln \frac{b^*}{1-a^*} + (1 - b^*) \ln \frac{1-b^*}{a^*}}{(\phi_1 - \phi_0) \mathbb{E}\big[\sum_{n=1}^{|S_t|} t_{n|\mathcal{H}_1}\big] + \frac{1}{2}(\phi_0^2 - \phi_1^2) \mathbb{E}\big[|S_t|\big]}. \quad (10)$$

Similarly, the average number of sensing rounds under $\mathcal{H}_0$, i.e., $\mathbb{E}[N \,|\, \mathcal{H}_0]$, can be derived.

Eqs. (8), (9), and (10) indicate that the average number of sensing rounds $\mathbb{E}[N]$ depends on: (i) the average number of sensors within the fusion range, which can be easily calculated as $\mathbb{E}[|S_t|] = \rho \pi R_f^2$, under the assumption of the point Poisson distribution of sensors, i.e., $|S_t| \sim Poi(n; \rho \pi R_f^2)$, and (ii) the sum of their reported test statistics, i.e., $\mathbb{E}[\sum_{n=1}^{|S_t|} t_{n|\mathcal{H}_k}]$.

D. Approximation of the Sum of Test Statistics

Let $T_{S(\rho, R_f)}$ denote the sum of the test statistics measured at the sensors within the fusion radius R_f from the WM transmitter, in the network of sensor density ρ. Then, under $\mathcal{H}_1$, it can be approximated as:

$$\begin{aligned}\mathbb{E}\big[T_{S(\rho, R_f)}\big] &= \mathbb{E}\Big[\sum_{n \in S_t} T_{n|\mathcal{H}_1}\Big] \\ &= \mathbb{E}\Big[\sum_{n \in S_t} \mathcal{N}(P_n + N_o, \sigma_n^2)\Big] \\ &\approx \mathbb{E}\Big[\sum_{n \in S_t} P_n\Big] + \mathbb{E}\Big[\sum_{n \in S_t} N_o\Big], \end{aligned} \quad (11)$$

where P_n is the received primary signal strength at sensor n and $S_t \equiv S(\rho, R_f)$ for brevity. The approximation in Eq. (11) is made based on the fact that the measurement errors of the energy detector is relatively smaller than the average received primary signal strength, i.e., $\sigma_n^2 \ll P_n + N_o$.

Based on Eq. (11), we now focus on approximation of the sum of received primary signal strengths, which can be rewritten as $\mathbb{E}[\sum_{n \in S_t} P_n] = P_o\, \mathbb{E}[\sum_{n \in S(\rho, R_f)} g(d_n) e^{X_n} e^{Y_n}]$ where P_o is the primary's transmit power, $g(d_n)$ is the sensor n's channel gain due to path-loss, i.e., $g(d_n) = (d_o/d_n)^\alpha$, and e^{X_n} and e^{Y_n} are the channel gains from shadowing and multi-path fading, respectively. We approximate the sum of channel gains due to path-loss, denoted by $\mathcal{G}_\Sigma(\rho, R_f) = \sum_{n \in S(\rho, R_f)} g(d_n)$, as a log-normal random variable.

Denote $\mathcal{G}_\Sigma(\rho, R_f) \sim Log\text{-}\mathcal{N}(\mu_G, \sigma_G^2)$. Then, the p.d.f. of $\mathcal{G}_\Sigma(\rho, R_f)$ is given as:

$$p_{\mathcal{G}(\rho, R_f)}(x) = \frac{1}{x \sigma_G \sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu_G)^2}{2\sigma_G^2}\right), \quad (12)$$

where the μ_G and σ_G^2 have the following relationships [20]:

$$\begin{cases} m_1(\rho, R_f) = e^{\mu_G + \frac{1}{2}\sigma_G^2} \\ m_2(\rho, R_f) = e^{2\mu_G + \sigma_G^2}(e^{\sigma_G^2} - 1). \end{cases} \quad (13)$$

Here $m_k(\rho, R_f)$ is the k^{th} cumulant of $\mathcal{G}_{(\rho, R_f)}$, given as:

$$\begin{aligned}m_k(\rho, R_f) &= \rho \pi (R_f^2 - \epsilon^2) \int_\epsilon^{R_f} \frac{2r}{(R_f^2 - \epsilon^2)} g(r)^k \mathrm{d}r \\ &= \frac{2\rho\pi\, d_o^{k\alpha}}{(k\alpha - 2)} \left(\frac{1}{\epsilon^{k\alpha - 2}} - \frac{1}{R_f^{k\alpha - 2}}\right), \end{aligned} \quad (14)$$

where d_o is the reference distance and ϵ is the minimum separation between the primary transmitter and the sensors, which is set to $\epsilon = 75\,\mathrm{m}$ in our simulation.[2]

From Eqs. (13) and (14), the log-normal random variable $\mathcal{G}_\Sigma(\rho, R_f) \sim Log\text{-}\mathcal{N}(\mu_G, \sigma_G^2)$ can be approximated as:

$$\mu_G = \frac{1}{2} \ln\left(\frac{m_1^4}{m_1^2 + m_2}\right) \quad \text{and} \quad \sigma_G^2 = \ln\left(1 + \frac{m_2}{m_1^2}\right). \quad (15)$$

Therefore, from Eqs. (11) and (15), and by incorporating the effects of shadowing and multi-path fading assuming the fading is i.i.d. for each sensor, the sum of received primary power at the cooperating sensors S_t can be expressed as:

$$\mathbb{E}\Big[\sum_{n \in S_t} P_n\Big] = P_o \cdot \mathbb{E}[\mathcal{G}_\Sigma(\rho, R_f)] \cdot \mathbb{E}[e^X] \cdot \mathbb{E}[e^Y], \quad (16)$$

[2] This is reasonable because the probability that there exists at least one sensor within $\epsilon = 75\,\mathrm{m}$ from the WM transmitter is $1 - Poi(0; \rho\pi\epsilon^2) \approx 0.02$ given sensor density of $\rho = 1.25 \times 10^{-6}/\mathrm{m}^2$.

where $\mathbb{E}[e^X] = e^{\frac{1}{2}\sigma^2}$, $\sigma = 0.1\ln(10)\sigma_{dB}$, $\mathbb{E}[e^Y] = 1$, and $\mathbb{E}[\mathcal{G}_\Sigma(\rho, R_f)] = e^{\mu_G + \frac{1}{2}\sigma_G^2}$.

Then, from Eqs. (11) and (16), the sum of normalized test statistics, i.e., $t_n \triangleq T_n \cdot \sigma_n^{-1}$, can be expressed as:

$$\mathbb{E}\Big[\sum_{n=1}^{|S_t|} t_{n|\mathcal{H}_1}\Big] = \mathbb{E}\Big[T_{S(\rho,R_f)}\,\sigma_n^{-1}\Big] = \Big(P_o\, e^{\frac{1}{2}\sigma^2}\mathbb{E}[\mathcal{G}_\Sigma(\rho, R_f)] + N_o\rho\pi R_f^2\Big)\,\sigma_n^{-1}. \quad (17)$$

Finally, based on Eqs. (8) and (17), the first term in Eq. (7) for calculating the average number of sensing rounds $\mathbb{E}[N \,|\, \mathcal{H}_1]$ can be derived as:

$$\mathbb{E}[\lambda \,|\, \mathcal{H}_1] = \frac{1}{2}(\phi_0^2 - \phi_1^2)\,\rho\pi R_f^2 + (\phi_1 - \phi_0) \times \big(P_o\, e^{\frac{1}{2}\sigma^2}\,\mathbb{E}[\mathcal{G}_\Sigma(\rho, R_f)] + N_o\rho\pi R_f^2\big)\,\sigma_n^{-1}, \quad (18)$$

where $\phi_0 = \frac{N_o}{\sigma_n}$ and $\phi_1 = \frac{N_o + P_R}{\sigma_n}$ are the average normalized test statistics under both hypotheses.

The average number of sensing rounds $\mathbb{E}[N \,|\, \mathcal{H}_1]$ can be derived by substituting Eqs. (9) and (18) into Eq. (7).

E. Optimal Data-Fusion Range

Based on the analyses above, we now derive an optimal data-fusion range that minimizes the average detection delay, i.e., the number of sensing rounds needed to meet the detection performance requirements.

Proposition 1 *(Optimal Fusion Range) Let* $J(R_f) \triangleq \mathbb{E}[\lambda \,|\, \mathcal{H}_1]$ *in Eq.* (18)*. Then, the optimal fusion range that minimizes the average number of sensing rounds* $\mathbb{E}[N]$ *is given as:*

$$R_f^* = \arg\max_{R_f} J(R_f) = R_f\Big|_{\frac{\partial J(R_f)}{\partial R_f}=0} = \left(\frac{a_1(\alpha - 2)}{2a_2}\right)^{\frac{1}{\alpha}}, \quad (19)$$

where

$$a_1 = \frac{2(\phi_1 - \phi_0)P_o\, e^{\frac{1}{2}\sigma^2}\rho\pi d_o^\alpha}{\sigma_n(2-\alpha)}, \quad (20)$$

$$a_2 = \frac{1}{2}(\phi_0^2 - \phi_1^2)\rho\pi + \frac{(\phi_1 - \phi_0)N_o\rho\pi}{\sigma_n}. \quad (21)$$

Proof. We first prove the concavity of $J(R_f)$ and then solve the optimization problem to obtain the optimal R_f. The detailed proof is omitted due to space constraint.

IV. DeLOC: The Iterative Approach

We now introduce DeLOC, an iterative algorithm that expedites the detection of small-scale primary signals via joint data-fusion and location/transmit-power estimation. We first describe the estimation techniques, and then the proposed data-fusion rule and the iteration method employed by DeLOC.

A. Estimation Techniques

1) Estimation of WM Location: In DeLOC, the BS estimates and updates the WM's location based on the RSSs reported by the sensors. In particular, the BS employs a *weighted centroid method* proposed in [21], which estimates the WM's location via a weighted average of the sensors' locations, where the weight equals the corresponding sensor's report. The BS further refines the estimation via an exponential moving average over multiple sensing stages.

Algorithm 1 DeLOC: Algorithm for Joint Detection and Estimation of Small-scale Primary Users

At the end of a sensing period, the BS does the following

```
for Each triggering event do
    t ← 1 // Initialization
    while t ≤ MaxNumIter do
        t ← t + 1
        θ_t ← Receive sensing results from cooperating sensors S_t
        Λ_t ← Λ_{t−1} + λ_t^{f(t)} // Update the decision statistic
        if Λ_t ≥ B then
            A primary exists and hence returns the estimated location and transmit-power level
        else if Λ_t < A then
            A primary does not exist (i.e., the event is triggered by a ghost primary) and hence terminates the iteration
        else
            (ϑ̂_{t+1}, P̂_{o,t+1}) ← Estimate the location and transmit power of the primary transmitter
            R*_{f,t+1} ← Calculate the optimal fusion range
            S_{t+1} ← Select a set of sensors located within R*_{f,t+1} from the estimated primary transmitter location
            Schedule another sensing round and wait for the observation
        end if
    end while
    return No primary signal exists
end for
```

2) Estimation of Transmit Power: In DeLOC, the BS estimates the WM's transmit power based on its estimated location and the reported RSSs using the method proposed in [22]. Note that the test statics of the energy detector include both noise power and primary signal power [17]. Therefore, the received primary signal strength P_n needs to be estimated from the test statistic by subtracting the average noise power level from the measurements.

B. The Proposed Data-Fusion Rule

We propose a new data-fusion rule for DeLOC, a *weighted sequential probability ratio test* (WSPRT), to prevent the BS from making biased decisions in early stages. The idea is to assign smaller weights to the decision statistics in early stages, and gradually increase the weights as the location and transmit-power estimates become more accurate. Specifically, we use the following rule to update the decision statistic:

$$\Lambda_t = \Lambda_{t-1} + \lambda_t^{f(t)} \quad \text{where} \quad f(t) = \frac{1}{1 + e^{1-t}} \quad t \in \mathbb{N}, \quad (22)$$

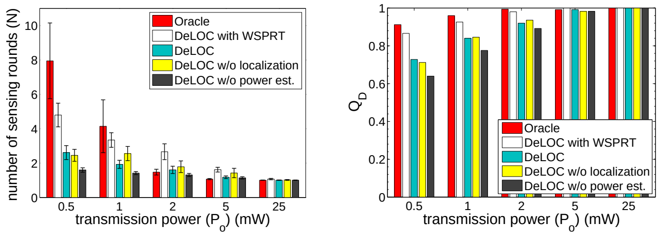
where we use the sigmoid function $f(t)$ such that the exponent of test statistics increases from 0.5 to 1 as t increases. Consequently, the test statistics in later stages count more in decision-making. **Algorithm 1** details DeLOC.

V. Performance Evaluation

In this section, we demonstrate the performance of DeLOC in comparison with other testing schemes.

A. Simulation Setup

In the simulation, we consider a realistic 802.22 environment where sensors are randomly distributed over a 30×30 km area. The average sensor density is set to $1.25/\text{km}^2$, as typically used in 802.22 WRANs [6]. We assume a WM randomly located in the area with effective transmit-power below 25 mW, as indicated by the measurement study in [11].



(a) Average detection delay (b) Achieved detection probability

Fig. 1. *Performance of* `DeLOC`: `DeLOC` (a) requires only a small number of sensing rounds for WM detection, and (b) achieves a high detection rate even for a very weak signal power, e.g., $P_o = 1\,\text{mW}$.

The maximum number of sensing rounds scheduled within the 2-second *channel detection period* (CDT) is limited to $\mathsf{MaxNumIter} = 100$.[3] The time duration for a single sensing period is $T_S = 1\,\text{ms}$. The path-loss exponent is $\alpha = 4$ and the shadow fading dB-spread is $\sigma_{dB} = 5.5\,\text{dB}$ (typically assumed for rural areas). The triggering threshold in `DeLOC` is configured as $\xi = N_o + 3.5\,\sigma_n$ to avoid frequent false-triggering. The simulation results are obtained from 5×10^3 randomly-generated topologies.

B. *Performance of* `DeLOC`

To demonstrate the efficacy of `DeLOC`, we compare its performance with the other four testing schemes under the detection constraints $Q_{FA}, Q_{MD} \leq 0.01$. As shown in Fig. 1, when the WM's transmit-power increases, the detection performance (with respect to delay and detection rate) increases for all testing schemes. We make three additional observations.

First, Fig. 1(a) shows that the average number of sensing rounds for decision-making is below 10, which may take only $100\,\text{ms}$ as the BS can schedule sensing periods as frequently as every $10\,\text{ms}$, i.e., one MAC frame size in 802.22. In addition, the detection probability of `DeLOC` with WSPRT meets the detection requirement of 802.22, i.e., $Q_{MD} \leq 0.1$, even for a very weak transmit-power of $1\,\text{mW}$, as indicated in Fig. 1(b).

Second, Fig. 1(b) shows that `DeLOC` with weighted SPRT (WSPRT) performs close to Oracle (which assumes known location and transmit power) in terms of detection rate, and outperforms all other schemes that use regular SPRT. As mentioned earlier, the SPRT in `DeLOC` often makes a wrong decision (mis-detection of a WM) in early detection stages based on many noisy reports due to the inaccurate location and power estimates. `DeLOC` with WSPRT mitigates this problem by discounting the decision statistics in early stages.

Third, Fig. 1(b) shows that `DeLOC` without localization outperforms the one without transmit-power estimation. This is because the power estimation plays an important role in finding the optimal fusion range, and therefore, the error in power estimation results in significant performance degradation. On the other hand, the location-estimation error is small compared with the typical fusion range, and thus it does not cause significant performance degradation.

These simulation results clearly demonstrate that the joint design of data-fusion and location & power estimation maximizes the benefits of spatial-temporal sensing for detecting small-scale primaries, such as WMs in 802.22.

[3]This is reasonable since the BS can schedule sensing as frequently as once every $10\,\text{ms}$, i.e., one MAC frame size in 802.22.

VI. Conclusion

The detection of small-scale primary signals is an important and challenging problem in realizing opportunistic spectrum access in CRNs. To solve this problem, we proposed a novel spatio-temporal fusion scheme that exploits (i) spatial diversity by cooperative sensing with an optimal fusion range, and (ii) temporal diversity by scheduling a series of sensing stages with an optimal stopping time. We (a) modeled the detection problem as a hypothesis test, (b) approximated the sum of sensor readings as a log-normal random variable, and then (c) solved a convex optimization problem, to obtain the optimal fusion range that minimizes the average detection delay. We also proposed a new sensing algorithm called `DeLOC` that iterates between cooperative sensing and location/transmit-power estimation to further improve the sensing performance under realistic settings. Our evaluation results show that `DeLOC` reduces the detection delay significantly while meeting the detection requirements.

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