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DETECTION OF DYNAMIC PRIMARY USER WITH COOPERATIVE SPECTRUM SENSING

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ABSTRACT

In this paper we demonstrate that existing cooperative spectrum sensing formulated for static primary users cannot accurately detect dynamic primary users regardless of the information fusion method. Performance error occurs as the sensing parameters calculated by the conventional detector result in sensing performance that violates the sensing requirements. Furthermore, the error is accumulated and compounded by the number of cooperating nodes. To address this limitation, we design and implement the duty cycle detection model for the context of cooperative spectrum sensing to accurately calculate the sensing parameters that satisfy the sensing requirements. We show that longer sensing duration is required to compensate for dynamic primary user traffic.

***Index Terms*—** Cognitive radio, spectrum sensing, cooperating spectrum sensing, dynamic primary user, duty cycle

1. INTRODUCTION

Cognitive radio promotes the concept of dynamic spectrum access to improve spectral utilisation efficiency [1]. The technology permits non-licensed, secondary users (SU) to access spectrum owned by licensed, primary users (PU) while restricting interference to PU activity. Spectrum sensing is a key component to cognitive radio as SU must accurately detect the presence/absence of PU signals [1]. Spectrum sensing poses numerous challenges, and often multiple SU must cooperate to achieve the target sensing requirements.

Cooperative spectrum sensing (CSS) is achieved where individual nodes of a SU network conduct *local* spectrum sensing and combine the local performance at the network level forming a *global* sensing performance. CSS can be implemented with varying network topologies, ranging from a de-centralised and distributed system to a centralised and infrastructure based system [1, 2]. For this study we focus on the centralised topology where SU nodes transmit their local sensing information to a central coordinator for information fusion, similar in [2].

Existing spectrum sensing studies are formulated using the conventional signal model of *static* PU, where the PU remains in a constant state (either ON or OFF) during the entire sensing period [1, 3]. However, PU traffic is often described using channel state probabilities or as a random process [3, 4] and such probabilistic modelling implies it is possible that PU is *dynamic* and changes state during the sensing period. A dynamic PU is only active for a fraction of the sensing period (know as the *duty cycle*), and this behaviour invalidates the signal model of the conventional, static PU [5]. Various studies and our prior work have demonstrated that detectors formulated for static PU cannot accurately detect dynamic PU as the sensing duration and decision threshold results in incorrect sensing performance [4–6].

Existing analyses into dynamic PU based on primary user traffic have mainly focused on a single SU sensing a single PU channel. To the best of our knowledge, no studies have investigated the detection performance of conventional CSS when sensing dynamic PU. CSS implies that performance error of a single node will be compounded by the number of cooperating nodes. Furthermore, different fusion rules react differently to this performance error. Thus it is crucial to investigate the severity of this phenomenon and address this problem.

In this paper we propose a framework for implementing the *duty cycle detector* (DCD) [4] previously developed for single user in the context of CSS to accurately compute the sensing performance and sensing parameters. We also analyse the sensing performance of various existing CSS fusion rules when sensing dynamic PU. The remainder of this paper is organised as follows: Section 2 briefly outlines two fusion rules used in CSS. Section 3 analyses the performance error of conventional hard fusion CSS and implements the DCD for the context of CSS. Section 4 performs similar analyses and implementation for soft fusion, while Section 5 concludes this paper.

2. CONVENTIONAL CSS

Sensing performance for detecting the presence of a PU can be measured by the probability of detection P_D and probability false alarm P_F. *Global* sensing performance (P_{Dg} and P_{Fg}) of the SU must satisfy the global sensing requirements (P_{DR} and P_{FR}), such that $P_{Dg} \geq P_{DR}$ and $P_{Fg} \leq P_{FR}$. When CSS is employed, each node can employ shorter sensing durations to achieve the desired global requirements due to cooperative gain [1, 2].

Hard fusion and soft fusion are two categories of information fusion rules in conventional CSS. Without lack of generality, we investigate one rule for each category: *OR-rule* and *equal gain energy fusion* (EF). We denote the following notation, subscript l for *local*, g for *global*, R for *required*, superscript O for *OR* rule and E for *EF* rule.

2.1. Hard Fusion Rule

For hard fusion, each SU node conducts local sensing using a sensing detector and generates a binary decision of either PU absent or present. This decision is transmitted to the central coordinator where the number of nodes indicating PU present is counted. The coordinator declares a PU is detected across the SU coverage zone when the number of local detections exceeds a specific cooperative threshold [2]. The local sensing performances for individual nodes are denoted as P_{Fl} and P_{Dl} for local P_F and P_D, respectively. We assume the PU signal observed at each SU is independent and identically distributed hence the local sensing performance are also identical.

OR rule is an example of hard fusion, where the coordinator declares PU present when *any* nodes detect an occupied channel. This rule places greater emphasis on PU protection and minimises the probability of missed detection. The global and local detection performances are relates as [2]

$$P_{Fg}^{O} = 1 - (1 - P_{Fl}^{O})^{n}\,, \tag{1}$$

$$P_{Dg}^{O} = 1 - (1 - P_{Dl}^{O})^{n}\,, \tag{2}$$

where n is the number of cooperating nodes. The local requirements P_{DRl}^{O} and P_{FRl}^{O} that can achieve the global requirements of P_{FR} and P_{DR} are given as [2]

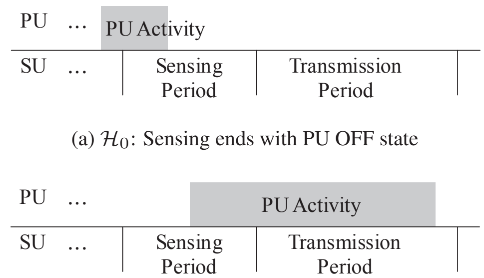
$$P_{FRl}^{O} \leq 1 - \sqrt[n]{1 - P_{FR}}\,, \tag{3}$$

$$P_{DRl}^{O} \geq 1 - \sqrt[n]{1 - P_{DR}}\,. \tag{4}$$

2.2. Soft Fusion Rule

When soft fusion is implemented, each SU node calculates a test statistic using the local detector and transmits the test statistic to the central coordinator [7]. The coordinator then combines the local test statistics into a single global test statistic and compares to the global threshold. Global performance is then computed by comparing the distribution of the global test statistic with the global threshold. We consider the energy fusion (*EF*) method with equal gain weighting for demonstration [7]. The local test statistic calculated by node j is denoted as $Y_{l,j}^{E}$ and the global test statistic is the summation of test statistic for all n nodes,

$$Y_{g}^{E} = \sum_{j=1}^{n} Y_{l,j}^{E}\,. \tag{5}$$



(a) $\mathcal{H}_0$: Sensing ends with PU OFF state

(b) $\mathcal{H}_1$: Sensing ends with PU ON state

Fig. 1. Examples of dynamic PU activity, with detection hypothesis based on last state during sensing.

3. DCD IMPLEMENTATION FOR HARD FUSION

3.1. Signal Model

A dynamic PU signal can be modelled as a two-state random process with exponential holding times of mean duration μ_0 and μ_1 for OFF and ON states respectively [3–5]. As the traffic model is random, it is possible that the SU observes multiple PU states during the sensing period of duration τ, as illustrated in Fig. 1.

The last observed state of a dynamic PU most closely represent the state of the PU when transmission period starts. Therefore the detection hypotheses for a dynamic PU is based on the last PU state [4]: SU declares null hypothesis $\mathcal{H}_0$ when the end state is OFF (Fig. 1a), and declare the alternate hypothesis $\mathcal{H}_1$ when the end state is ON (Fig. 1b).

Duty cycle D is defined as the fraction of the sensing period occupied by a PU signal, $D_i = \frac{C_i}{\tau}$, where C_i is the cumulative duration of ON states for hypothesis $\mathcal{H}_i$, for $i = 0, 1$. An in depth statistical derivation for the distribution of duty cycle is outlined in [4].

This study focuses on investigating the effect of PU traffic on the performance of CSS. We implement the energy detector and model both noise and PU signal as zero mean, Gaussian distributed with variance σ_n^2 and $\sigma_s^2 = \gamma\sigma_n^2$, respectively, where γ is PU SNR [3, 8]. Each SU receives an independent observation of the PU signal exhibiting the same D and γ. Sensing performance of are measured by the probability that test statistic Y_{Di} exceeds decision threshold λ for hypotheses $\mathcal{H}_i$

$$P_{FD}(\tau, \lambda) = P(Y_{D0} > \lambda)\,, \tag{6}$$

$$P_{DD}(\tau, \lambda) = P(Y_{D1} > \lambda)\,. \tag{7}$$

P_{FD} and P_{DD} of DCD measure the performance of detection during the sensing period. However, these metrics no longer indicate the actual interference to PU and lost opportunity of SU during the transmission period that follows sensing. Investigating the effect of PU traffic during the transmission period is beyond the scope of this study.

3.2. Conventional Hard Fusion Analysis

The conventional detector assumes PU to be completely absent under $\mathcal{H}_0$ (equivalent to $D = 0$) and fully present under $\mathcal{H}_1$ (equivalent to $D = 1$). It then calculates sensing parameters τ_c and λ_c assuming the conventional performance P_{Fc} and P_{Dc} satisfy the global requirements,

$$P_{Fc}(\tau_c, \lambda_c) = P_{FR}\,,\ P_{Dc}(\tau_c, \lambda_c) = P_{DR}\,. \qquad (8)$$

We analyse the performance error of conventional hard fusion CSS using the following framework,

1. PU and SU sets P_{FR} and P_{DR}.
2. SU assigns n, calculates conventional τ_c and λ_c.
3. Calculate true P_{Fg} and P_{Dg} at τ_c and λ_c.
4. Investigate error in P_F and P_D for different n.

This framework is also adapted for soft fusion in Section 4.

In hard fusion, each SU senses a PU of channel bandwidth W exhibiting duty cycle D and computes the test statistic Y_D. Y_D is Gamma distributed conditioned to the observed D [4],

$$Y_D|D \sim \Gamma\left(\frac{\tau W}{2}, 2\sigma_n^2\left(1+\gamma D\right)\right)\,. \qquad (9)$$

D varies between observation, hence the density functions of Y_{D1} and Y_{D0} are calculated by averaging the condition density of $Y_D|D$ over the probability of D to get [4],

$$f_{Y_{D_i}}(x) = \int_{y=0}^{1} f_{Y_{D_i}|D_i=y}(x) f_{D_i}(y)\,dy\,. \qquad (10)$$

$f_X(x)$ denotes the probability density function of X.

Local sensing requirements for hard fusion are calculated using (3) and (4) and applied to (8) to get τ_c^O and λ_c^O. Here the conventional performance becomes P_{Fl} and P_{Dl} to achieve requirements of P_{FRl} and P_{DRl}. τ_c^O is then used to generate the true distribution of Y_{Di} with (10) and the true detection performance computed by applying λ_c^O into (6) and (7). Here P_{FD} and P_{DD} becomes true local performance P_{Fl}^O and P_{Dl}^O, and the global performance are calculated with (1) and (2). The calculated P_{Fg}^O and P_{Dg}^O are the actual performance achieved by the conventional detector when sensing a dynamic PU.

A closed form solution for the Gamma distribution is not possible to solve explicitly for τ and λ in (6) and (7) hence the algorithm in [4] is used to numerically solve for τ_c^O and λ_c^O in (8). To analyse the performance of conventional CSS and later implement DCD, we simulate the PU signal SNR as $\gamma = -10$dB, $W = 200$kHz and sensing requirements as $P_{FR} = 0.1$ and $P_{DR} = 0.9$. The number of cooperating nodes range between $n = 1$ (equivalent to non-cooperative sensing) to $n = 30$. Noise power is equalised to $\sigma_n^2 = 1$. Four

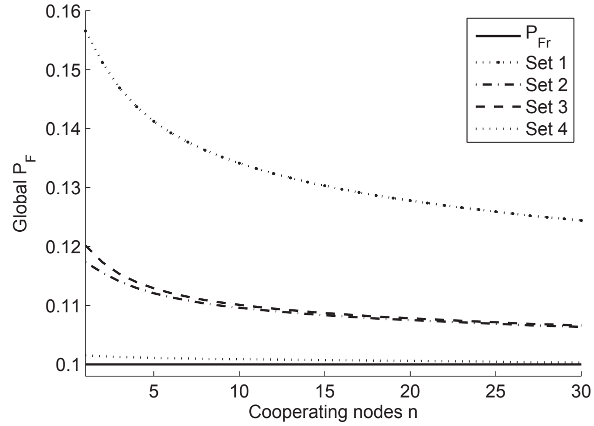


Fig. 2. *OR* rule P_{Fg}^O decreases towards P_{FR} with increasing n but never satisfy the requirements.

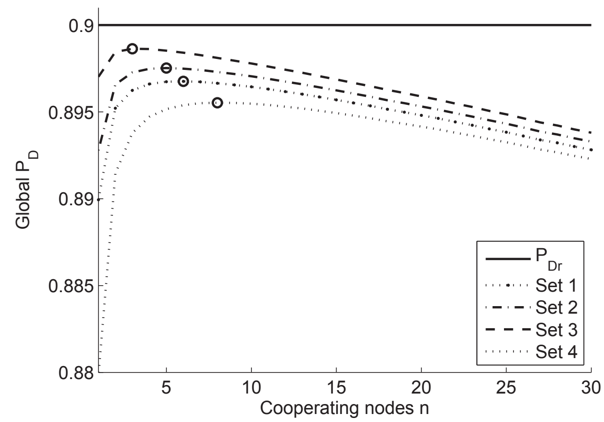


Fig. 3. *OR* rule P_{Dg}^O initially increases towards P_{DR} with greater n but exhibits a local maximum and then decreases.

sets of PU traffic $\{\mu_0, \mu_1\}$ are chosen for analysis: $\{0.25, 1\}$, $\{1, 0.25\}$, $\{1, 10\}$, $\{10, 1\}$.

Fig. 2 shows that the actual P_{Fg}^O achieved by *OR* rule CSS is significantly greater than P_{FR}, especially at lower n. Increasing n reduces the error between P_{Fgc}^O and P_{FR}, however the error always exists. Comparing between PU traffic we see that longer μ_0 results in smaller error in P_F.

Fig. 3 shows that increasing n initially increases P_{Dg}^O, but never satisfies P_{DR} and decreases after a maximum is reached (indicated by circle markers). This implies that performance error cannot be simply alleviated with larger n; error in a single node is accumulated and compounded by the number of cooperating nodes.

τ_c and λ_c are inaccurate when the PU is dynamic as the conventional detector does not account for D. Therefore P_{Fc} and P_{Dc} achieved using τ_c and λ_c will not satisfy the requirements and result in performance errors ($P_{Fc} > P_{FR}$,

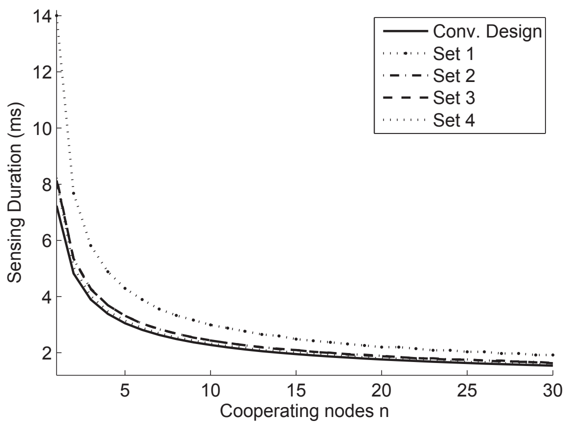


Fig. 4. τ_r^O that satisfies the detection requirements decreases with larger n. τ_c^O is shorter than τ_r^O but cannot satisfy the requirements.

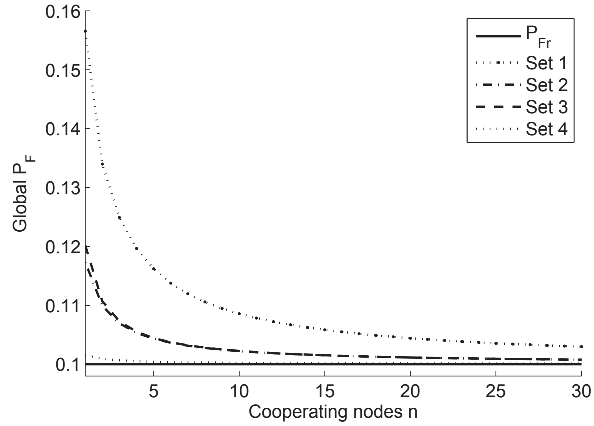


Fig. 5. P_{Fg}^E for *EF* rule decreases with larger n but always greater than P_{FR}.

$P_{Dc} < P_{DR}$). CSS must incorporate the effect of PU traffic when detecting dynamic PU, therefore we implement DCD to accurately compute parameters that satisfy sensing requirements and account for of PU traffic.

3.3. DCD Hard Fusion Implementation

DCD proposed in [4] was designed for a single SU sensing a single dynamic PU. We now design and implement the detector for hard fusion CSS. DCD integrates the distribution of D into Y_D before comparing with λ. The sensing parameters τ_r and λ_r must ensure global requirements P_{FR} and P_{DR} are met. Longer τ is required if the sensing performance are to exceed the requirements, however shorter τ is desired for network layer objectives [3,4]. Therefore τ_r and λ_r are designed such that the performance meet the requirements at equality,

$$P_{FD}(\tau_r, \lambda_r) = P_{FR}\,,\; P_{DD}(\tau_r, \lambda_r) = P_{DR}\,. \qquad (11)$$

DCD is implemented on each local SU node and makes a local decision using sensing parameters calculated by Step 1 and 2 of the framework in Section 3.2. P_{FRl}^O and P_{DRl}^O are calculated from (3) and (4) for a given n, and parameters τ_r^O and λ_r^O are adapted from (6) and (7) such that

$$P_{FD}(\tau_r^O, \lambda_r^O) = P_{FRl}^O\,,\; P_{DD}(\tau_r^O, \lambda_r^O) = P_{DRl}^O\,. \qquad (12)$$

Satisfying the local requirements at equality will also satisfy the global requirements at equality.

Implementing DCD ensures the local requirements (hence global requirements) are satisfied. Fig. 4 plots τ_r^O for different PU traffic for increasing n. The detector requires longer τ_r^O compared to the conventional sensing duration τ_c^O to compensate for increased D under $\mathcal{H}_0$ and decreased D under $\mathcal{H}_1$. This is a necessary compromise as the conventional sensing τ_c^O cannot satisfy the detection requirements. Comparing between PU traffic parameters we see that μ_0 has greater effect on τ_r^O with larger μ_0 resulting in shorter τ_r^O.

4. DCD IMPLEMENTATION FOR SOFT FUSION

The global test statistic Y_g^E defined in (5) of the *EF* rule is the summation of n local test statistic following the distribution in (9) conditioned to observed D. Since D is constant across all nodes, the conditional distribution of $Y_g^E|D$ is defined as

$$Y_g^E|D \sim \Gamma\left(\frac{n\tau W}{2}, 2\sigma_n^2(1+\gamma D)\right)\,. \qquad (13)$$

The average distribution of Y_g^E is calculated similar to (10).

4.1. Conventional Soft Fusion Analysis

The conventional detector for soft fusion assumes $D = 0, 1$ under $\mathcal{H}_0$ and $\mathcal{H}_1$ respectively in (13). Therefore it calculates parameters τ_c^E, λ_c^E to achieve the global performance as

$$P_{Fg}^E(\tau_c^E, \lambda_c^E) = P_{FR}\,,\; P_{Dg}^E(\tau_c^E, \lambda_c^E) = P_{DR}\,. \qquad (14)$$

However, D is a random variable when PU is dynamic and applying τ_c^E and λ_c^E to the test statistic in (13) results in performance error similar to hard fusion rules.

Performance error of the *EF* rule show similar results as the *OR* rule. Fig. 5 observes larger P_{Fg}^E at low n and decrease for higher n. P_{Dg}^E in Fig. 6 is initially lower at low n and increases with n. The rate of improvement of the *EF* rule for P_{Fg}^E and P_{Dg}^E with respect to increasing n is better than *OR* rule and P_{Dg}^E does not exhibit a maximum.

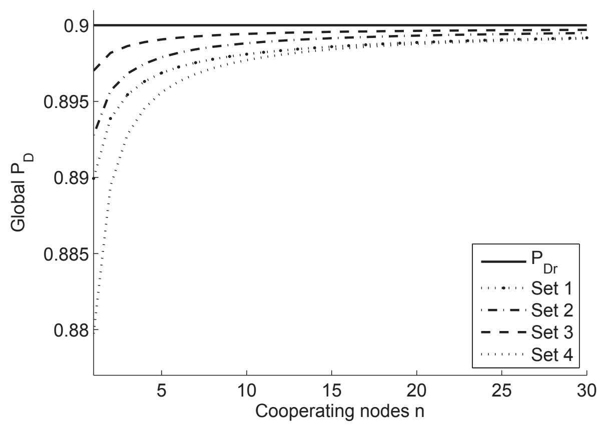


Fig. 6. P_{Dg}^E for *EF* rule increases with larger n but always less than P_{DR}.

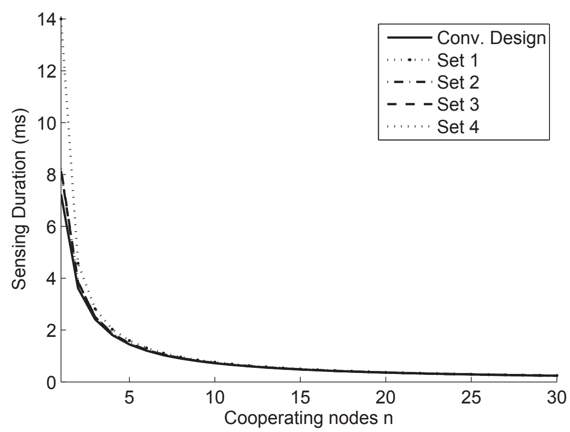


Fig. 7. τ_r^E decreases significantly with larger n and is less affected by PU traffic.

4.2. DCD Soft Fusion Implementation

Soft fusion implements DCD at the central coordinator after local test statistics of each node are combined using (5). Sensing parameter calculations for *EF* rule follow the same procedure with (6) and (7), where Y_{D0} and Y_{D1} are Y_{g0}^E and Y_{g1}^E with distribution given in (13). From (11), P_{FD}^E and P_{DD}^E are the global performance that must satisfy the global requirements of P_{FR} and P_{DR} such that,

$$P_{FD}^E(\tau_r^E, \lambda_r^E) = P_{FR}\,,\; P_{DD}^E(\tau_r^E, \lambda_r^E) = P_{DR}\,. \qquad (15)$$

Similar to hard fusion, sensing duration of each node τ_r^E and global decision threshold λ_r^E are calculated numerically.

Fig. 7 shows that τ_r^E decreases more significantly with larger n compared to *OR* rule. We also see that τ_r^E is less affected by PU traffic and the difference between τ_c^E is greatly reduced at larger n.

5. CONCLUSION

In conclusion, we demonstrated that the conventional detector creates performance error by violating the sensing requirements of a dynamic primary user. The calculated sensing parameters can only satisfy the requirements of a static primary user, regardless of fusion rule. Furthermore, multiple secondary users cooperating implies that performance error of a single node is compounded by the number of cooperating nodes. To compensate for this short fall, we designed and implemented the duty cycle energy detector for the context of cooperative spectrum sensing using hard and soft fusion rules. We showed that sensing requirements can be met with no accumulated error at the expense of longer sensing duration.

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