Collaborative Quickest Spectrum Sensing via Random Broadcast in Cognitive Radio Systems

Husheng Li, Huaiyu Dai, and Chengzhi Li

***Abstract*—Quickest detection is applied in spectrum sensing in cognitive radio systems when multiple secondary users collaborate with limited communication time slots. When the transmissions of sensing results are not coordinated to avoid confliction, random broadcast is used to exchange information. A necessary condition for the optimal broadcast probability, as a function of the log likelihood ratio of local observation, is obtained using variational analysis. To alleviate the difficulty of computing the optimal broadcast probability, a simple threshold broadcast scheme is proposed. Simulation shows that the proposed threshold broadcast scheme can achieve substantial performance gain (less than 60% in detection delay for the same false alarm rate) over schemes of random broadcast without regulation and single-user spectrum sensing.**

***Index Terms*—Cognitive radio, spectrum sensing, quickest detection, random broadcast.**

I. Introduction

SPECTRUM sensing is a key issue in cognitive radio systems [15] which are becoming the focus of study in the community of wireless communications. In cognitive radio systems, secondary users (without license) must detect the emergence of primary users and then quit the corresponding licensed frequency band as quickly as possible. An oversensitive secondary user may unnecessarily interrupt its own communication while a dull spectrum sensor may cause substantial interference to primary users.

A novel framework of spectrum sensing using the theory of quickest detection [4] [14] [17] (coined as *quickest spectrum sensing*) has been exploited in recent years [5] [12] [23]. Essentially, quickest detection is to detect the change in the distribution of observations, being useful in many areas like financial analysis, econometrics and network security. It is thus natural to introduce quickest detection into the task of spectrum sensing to detect the change of spectrum occupancy. In [5] and [12], cumulative sum (CUSUM) test, originally proposed in [16] in 1954, is applied to detect the emergence of primary users. Bayesian quickest detection is considered in [23] based on the assumption of *a priori* information about primary user activity. All these works show that the quickest detection can effectively improve the agility and robustness of the spectrum sensing.

However, the above papers are all based on single-user observations. Due to many random factors in wireless environments, e.g. fast fading and shadowing, single-user spectrum sensing may not be reliable. Therefore, collaborative spectrum sensing has attracted great interest, which allows the collaboration among multiple secondary users to enhance the robustness of spectrum sensing [1] [8] [9] [21]. Motivated by the collaborative spectrum sensing, collaborative quickest detection is studied in [11], in which the communication delay of sensing results is considered. However, most studies assume a perfect coordination for the information exchange. For example, in [11], a spanning tree is assumed to be generated for information exchange and the communication is assumed noiseless and conflictionless. Such a perfect coordination may not be reasonable in practical systems, especially in mobile ad hoc networks, since organizing such a coordination may bring substantial overhead, and its maintenance may require further efforts if the network topology changes rapidly. Therefore, there is a pressing need to study the collaborative spectrum sensing under imperfect coordination.

In this paper, we study the collaborative quickest spectrum sensing without an explicit coordination for the information exchange[1]. The timing structure for the spectrum sensing, information exchange and data transmission is illustrated in Fig. 1, whose detail will be explained later. We consider the case in which *there are only limited time slots in a reliable common control channel (in a band other than the licensed band) for the secondary users to exchange the information of spectrum sensing and there is no coordination to avoid transmission collisions*. The cooperation of spectrum sensing is based on broadcasting the local observations or statistics in a randomly chosen time slot. Such a scenario is particularly suitable for mobile cognitive radio networks, e.g., vehicular communication networks using cognitive radio links, in which it is difficult to coordinate the communication for spectrum sensing due to the lack of a long-term collaboration. Note that carrier sense multiple access (CSMA) is a traditional random multiple access approach to resolve collisions among multiple users without an explicit coordination. The random broadcast scheme considered in this paper is similar to a CSMA without the mechanism of collision avoidance (CA). Assume that CSMA without CA is used. At the beginning of each information exchange period in the control channel,

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[1]Note that distributed quickest detection for general purposes has been studied in [3] [6] [19] [20]. They all assume coordinated communications which incur no collision.

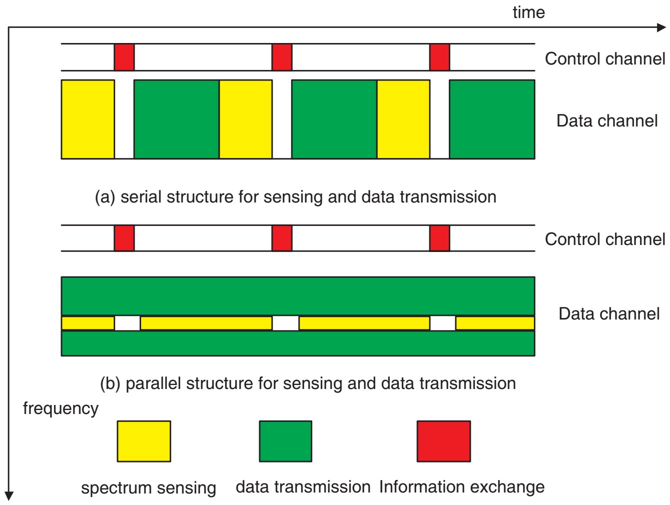

Fig. 1. Timing structure of spectrum sensing and broadcast.

there exist multiple secondary users intending to broadcast their observations, with a large probability. By knowing that a collision must occur if they all transmit in the first time slot, these secondary users carry out random backoffs in CSMA. This is similar to randomly choosing one time slot in our proposed scheme, which justifies the similarity between the CSMA without CA and the random broadcast. It is well known that the signaling of request-to-send (RTS) and clear-to-send (CTS) can improve the efficiency of CSMA. However, the transmission and reception of RTS and CTS incur a significant overhead (it requires at least three time slots to complete the transmission of one message) to the procedure of collaborative spectrum sensing since the time used for exchanging information is very limited and each message is very short (e.g. 32 bits for representing a likelihood ratio). Therefore, for minimizing the overhead, we adopt the simple approach of random broadcast.

The key issue of the proposed random broadcast based collaborative quickest spectrum sensing is *for each secondary user to determine whether to broadcast based on its current observation and the population of secondary users nearby.* Note that such a problem has been addressed for distributed sensor networks (coined censoring sensors) [18] [22]. However, no study has been focused on the distributed quickest detection, which is delay-sensitive, to the authors' best knowledge. If always broadcasting for every observations (we call it *broadcast without regulation*), too many collisions may incur a performance degradation; on the other hand, if always not broadcasting (i.e. single-user spectrum sensing), then we lose the performance gain of collaboration. Therefore, we need to find the optimal tradeoff between exchanging more information and avoiding broadcast collisions. Using the asymptotic analysis[2] (both in the number of secondary users and the number of available time slots) and variational analysis, we obtained a theoretical characterization for the optimal broadcast probability (Prop. 1). Based on the necessary condition, an iterative algorithm is proposed to compute the optimal broadcast probability. Due to the prohibitive difficulty of obtaining an explicit expression of the optimal broadcast probability, an intuitive and simple *threshold broadcast* scheme is proposed. Numerical results show that the threshold broadcast scheme coincides with the optimal broadcast probability obtained from numerical iterations and can substantially improve the performance of spectrum sensing (reducing at least 40% of the detection delay), compared with the schemes of random broadcast without regulation and single-user spectrum sensing.

The remainder of this paper is organized as follows. The system model and known results about quickest detection are introduced in Section II. In Section III, the necessary condition for the optimal broadcast probability in collaborative quickest detection is derived and a simple threshold broadcast scheme is proposed. Numerical results and conclusions are provided in Sections IV and V, respectively.

II. System Model and Known Results

In this section, we introduce the system model and known results about single-user quickest spectrum sensing.

A. System Model

Suppose that there are N secondary users in a cognitive radio system. These secondary users share the same spectrum sensing period such that the signal of secondary users will not be confused with that of primary users. The observations[3], denoted by $X_n(t)$ for user n at sample period t, are mutually independent for different secondary users and different sample periods. For simplicity, we assume that the distributions of observations for different secondary users are the same, which is reasonable if all the secondary users are geographically close to each other. We assume that there is no primary user at the beginning and then primary users emerge at an unknown time. Therefore, the distribution of observations satisfies hypothesis H_0 at the beginning and changes to H_1 at the unknown change time. We further assume that the probability density functions for both hypotheses H_0 and H_1 exist and are denoted by f_0 and f_1, respectively. Before the change, the secondary users can use the licensed band for data transmission[4], and they must quit the licensed band after the change. The task of these secondary users is to detect the emergence of primary users as quickly as possible, i.e. incurring a minimal detection delay while keeping a reasonable false alarm rate. Note that the observation distributions may not be known in practical systems. In this case, we can apply heuristic statistics for the quickest spectrum sensing, similar to the quickest detection in Denial of Service (DOS) attack detection in computer networks [13], which is beyond the scope of this paper. Note that we consider only the detection of the emergence of primary users in this paper. Actually, the framework also

[2]Note that the asymptotic analysis is to facilitate the mathematical analysis and does not mean that the the practical system has infinitely many time slots for exchanging the information of spectrum sensing. As will be demonstrated in the numerical simulation results, the algorithm obtained from the asymptotic analysis is still valid even when there are only 5 time slots during the information exchange.

[3]We consider a generic observation, which could be received power or cyclostationary features.

[4]The details of resource allocation in the licensed band to these secondary users are beyond the scope of this paper.

applies for the detection of the disappearance of primary users with minor modifications.

We suppose that each secondary user is equipped with a wireless transceiver. Therefore, the secondary users can broadcast their current observations (or sufficient statistics) such that the performance of spectrum sensing can be improved. We assume that there are M time slots [5] for broadcasting the messages of spectrum sensing following each spectrum sensing period. We define $\alpha \triangleq \frac{N}{M}$, which represents the extent of congestion in the communication time slots. One secondary user can finish its broadcast within one time slot. For simplicity, we assume that each secondary user obtains one observation during the spectrum sensing period. For the general case of multiple observations per spectrum sensing period, these observations can be fused into a sufficient statistic.

For simplicity of analysis, the following assumptions are made for the broadcast:

- The secondary users are close to each other such that a broadcast can cover all users. This justifies the assumption of the identical observation distribution for all secondary users. Only one broadcast is allowed in each time slot. If two or more broadcasts are within one time slot, they will collide with each other and thus cannot be decoded.
- The quantization error and possible decoding error are ignored.
- There is no centralized controller or consensus mechanism to coordinate the broadcast of the secondary users. Therefore, the secondary users have to broadcast in a random manner, i.e. choosing a random time slot for broadcast.
- Since the spectrum sensing and data transmission must be multiplexed, the spectrum sensing can be interleaved with the data transmission either *serially* or *parallely*, as illustrated in Fig. 1. In the serial case, the spectrum sensing and data transmission are interleaved in time. Each data transmission follows a period of spectrum sensing. In this case, we can still incorporate the period of data transmission into the quickest spectrum sensing framework by setting the likelihood ratios during the data transmission to be 1 (thus providing no information). Then, the spectrum sensing can be considered uninterrupted in time. In the parallel structure, the data transmission and spectrum sensing are carried out simultaneously, but in different portions of the frequency band, thus keeping the orthogonality of both procedures. For example, the secondary user can use orthogonal frequency division multiplexing (OFDM) and put zero power on the spectrum portion that is being sensed by the spectrum sensor. Some guard band or notch filter can be used to prevent the possible power leakage from the data transmission. This parallel structure is based on the assumption that the primary user must transmit within the spectrum portion being sensed by the secondary user. This is reasonable for TV band since the spectrum sensing can be focused on the frequency portion of TV pilots, which are always on once the TV system begins operation. Notice that, in both serial and parallel structures, we can assume that the spectrum sensing is uninterrupted in time and ignore the period of data transmission for the simplicity of discussion. Note that this does not mean that there is no data transmission in the cognitive radio system.
- The information exchange for collaborative spectrum sensing is carried out in a reliable common control channel, not in the licensed data band being sensed. Although the design of control channel in cognitive radio systems is a challenging problem, it is beyond the scope of this paper. We assume that each broadcast in the common control channel can be successfully received unless it collides with other broadcast. We also assume that the common control channel is not affected by the primary user's activities.

[5]They can also be M orthogonal channels in the frequency domain.

B. Known Results for Single-user Spectrum Sensing

For a single secondary user, CUSUM test [16] can be used to detect the emergence of primary users. The corresponding stopping time of claiming the change is given by (in this subsection, we drop the subscript of secondary users)

$$T^* = \inf \left\{ t \middle| m(t) \geq \gamma \right\}, \tag{1}$$

where γ is a predetermined threshold[6] and metric $m(t)$ is defined as

$$m(t) = \max \left(m(t-1) + l(t), 0 \right), \tag{2}$$

and $l(t)$ is the log likelihood ratio of observations, which is defined as

$$l(t) \triangleq \log \left(\frac{f_1(X(t))}{f_0(X(t))} \right). \tag{3}$$

Intuitively, T^* is the first time slot in which the metric $m(t)$ passes the threshold γ.

We use two metrics, namely average detection delay, denoted by D, and false alarm rate, denoted by F, which have been used in many studies [17], to measure the performance of quickest spectrum sensing. These metrics are defined as

$$\begin{aligned} D &= \text{esssup} \left(E\left[(T^* - T)^+ | \mathcal{F}_{T-1} \right] \right), & (4) \\ F &= P(T^* < T), & (5) \end{aligned}$$

where T is the change time and $\mathcal{F}_{T-1}$ is the filtration, namely the smallest σ-field with respect to observation history $X(0)$,...,$X(t-1)$. The esssup means the worst case of detection delay. Obviously, we desire small D and F. The details can be found in [4] [17].

When $\gamma \to \infty$, Brownian motion approximation based asymptotic analysis shows that, for the CUSUM test, the

[6]It is prohibitively difficult to find an explicit expression for the threshold used in the framework of quickest detection. Typically, a suitable threshold is determined by numerical simulations or experiments. In Section IV, we will provide ROC curves obtained from different thresholds. The optimal threshold can be determined by the ROC curves and the requirement of performance, e.g. the required detection delay and false alarm rate.

metrics can be approximated by [4] [17]

$$D \approx \frac{\gamma}{I_1}, \quad (6)$$

$$\log F \approx \frac{2\gamma I_0}{V_0}, \quad (7)$$

where, $\forall i = 0, 1$, I_i (V_i) is the expectation (variance) of log likelihood ratio under hypothesis i, i.e.

$$I_i = E_i\left[\log\left(\frac{f_1(X)}{f_0(X)}\right)\right], \quad (8)$$

$$V_i = E_i\left[\left(\log\left(\frac{f_1(X)}{f_0(X)}\right)\right)^2\right] - I_i^2, \quad (9)$$

where E_i means the expectation under hypothesis i.

To avoid dependence on the threshold γ, we use the following quantity as the asymptotic performance metric of quickest spectrum sensing:

$$\mathcal{M} \triangleq \frac{|\log F|}{D} \approx \frac{2|I_0|I_1}{V_0}. \quad (10)$$

Obviously, a larger $\mathcal{M}$ implies better performance (notice that $\log F$ is negative), i.e. the false alarm is decreased for the same average detection delay.

III. Random Broadcast

In this section, we discuss the random broadcast for collaborative quickest spectrum sensing, where the randomness is from both the decision of whether to broadcast and the time slot selection. We first derive a necessary condition for the optimal broadcast probability via asymptotic and variational analysis and then propose a simple threshold broadcast scheme.

A. Random Broadcast Scheme

Since there is no centralized controller or consensus mechanism for coordination, the only approach for the secondary users is to broadcast their information by selecting a random time slot. The procedure of random broadcast is given below.

1) At the end of the spectrum sensing period, each secondary user (say, user n) first determines whether to broadcast, based on the log likelihood ratio of $X_n(t)$. We denoted by $P_B(l)$, called *broadcast probability*, namely the probability to broadcast when the log likelihood ratio is l, which is assumed to be the same for all secondary users.
2) If a secondary user decides to broadcast, it broadcasts $l_n(t)$ in a randomly selected time slot. If there is no other secondary user broadcasting in the same time slot, all other secondary users will receive the information; if there is a collision, the colliding packets will be dropped.
3) At the end of time slot M, each secondary user collects the information received during this period and updates the metric of CUSUM test in (1) by summing the collected log likelihood ratios[7].

[7]Note that the secondary user transmits in a later time slot may obtain more samples and thus can update its transmission. This issue has been addressed in [7] but is out of the scope of this paper.

Assuming that N, M, f_1 and f_0 are all known[8], we can optimize $P_B(l)$ to maximize the asymptotic performance metric $\mathcal{M}$ in (10).

B. Asymptotic Analysis

We assume that the broadcast probability $P_B(l)$ is fixed and analyze the asymptotic performance metric $\mathcal{M}$, for which we need to obtain expressions of the quantities I_1, I_0 and V_0.

First, we analyze I_1. On defining probability (intuitively, it means the probability that a secondary user broadcasts when the true distribution is H_i)

$$\mathtt{p}_i = \int_{-\infty}^{\infty} P_B(l) f_i(l) dl, \qquad i = 0, 1, \quad (11)$$

and events $S_n \triangleq \{\text{broadcast of } l_n \text{ is successfully received}\}$ and $B_n \triangleq \{\text{user } n \text{ broadcasts}\}$, the average of log likelihood ratios that can be successfully received when the distribution is H_1 is given by ($I(S_n)$ is the characteristic function of event S_n)[9]

$$\frac{1}{N} E_1\left[\sum_{n=1}^{N} l_n I(S_n)\right] \to \exp(-\alpha \mathtt{p}_1) \int_{-\infty}^{\infty} l P_B(l) f_1(l) dl, \quad (12)$$

as $M, N \to \infty$ and $\frac{N}{M} = \alpha$. The derivation is provided in the appendix.

Then, we calculate I_0 and V_0. Similarly to (12), I_0, normalized by N, is asymptotically equal to

$$\frac{1}{N} E_0\left[\sum_{n=1}^{N} l_n I(S_n)\right] \to \exp(-\alpha \mathtt{p}_0) \int_{-\infty}^{\infty} l P_B(l) f_0(l) dl. \quad (13)$$

With more complicated calculation (the derivation is provided in the appendix), we obtain V_0, which is given by

$$\frac{1}{N} V_0 \to \exp(-\alpha \mathtt{p}_0) \int_{-\infty}^{\infty} l^2 P_B(l) f_0(l) dl + \exp(-\alpha \mathtt{p}_0) \Psi(\mathtt{p}_0, \alpha), \quad (14)$$

where

$$\begin{aligned} & \Psi(\mathtt{p}_0, \alpha) \\ \triangleq\ & \exp(\alpha \mathtt{p}_0) \lim_{N,M\to\infty, N/M=\alpha} (N-1)\frac{M-1}{M} \\ \times\ & \left(1 - \frac{2\mathtt{p}_0}{M}\right)^{N-2} - N\left(\left(1 - \frac{\mathtt{p}_0}{M}\right)^{N-1}\right)^2 \\ -\ & (1 + \alpha - 2\mathtt{p}_0\alpha + (\mathtt{p}_0\alpha)^2)\exp(-\alpha \mathtt{p}_0) \\ \times\ & \left(\int_{-\infty}^{\infty} l P_B(l) f_0(l) dl\right)^2. \end{aligned} \quad (15)$$

The convergence curves of I_1 and V_0 are plotted in Fig. 2, where we observe that I_1 converges very fast while V_0 converges much slower.

[8]When N is unknown (M is known to all secondary users since it is a part of the protocol), i.e. α is unknown, we can use threshold broadcast scheme, which will be proposed later, using fixed threshold for a wide range of α, as will be demonstrated in the section of numerical results.

[9]Note that secondary user n can always use its own observation; however, in the asymptotic case, the single observation is negligible since the received information increases in N; therefore, we can assume that all observations of a secondary user are from received broadcasts.

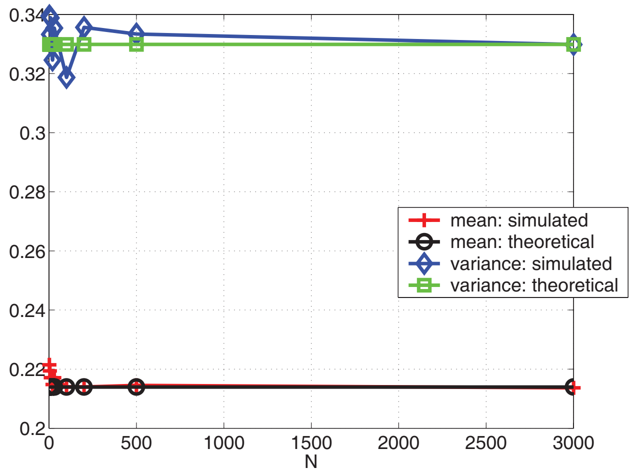

Fig. 2. Comparison between asymptotical and finite means and variances.

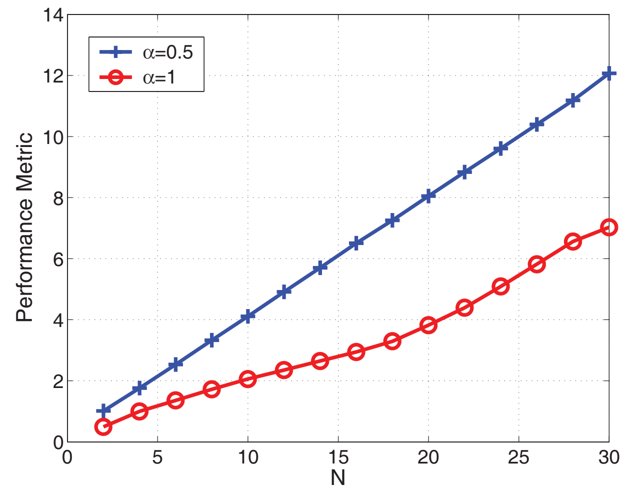

Fig. 3. Performance metric $\mathcal{M}$ versus N when $\alpha = 0.5$ and 1.

Based on the above analysis, the metric $\mathcal{M}$, normalized by N, is asymptotically given by

$$\lim_{N\to\infty} \frac{\mathcal{M}}{N} = \frac{2\mathcal{P}_1\mathcal{E}_0\mathcal{E}_1}{\mathcal{V}_0+\Psi}, \tag{16}$$

where

$$\Psi = -(1+\alpha-2\alpha \mathrm{p}_0 + (\alpha \mathrm{p}_0)^2)\mathcal{P}_0\mathcal{E}_0^2, \tag{17}$$

and

$$\left\{\begin{array}{lcl} \mathcal{P}_1 &=& \exp\left(-\alpha\int_{-\infty}^{\infty} P_B(l)f_1(l)dl\right) \\ \mathcal{P}_0 &=& \exp\left(-\alpha\int_{-\infty}^{\infty} P_B(l)f_0(l)dl\right) \\ \mathcal{E}_1 &=& \int_{-\infty}^{\infty} lP_B(l)f_1(l)dl \\ \mathcal{E}_0 &=& -\int_{-\infty}^{\infty} lP_B(l)f_0(l)dl \\ \mathcal{V}_0 &=& \int_{-\infty}^{\infty} l^2P_B(l)f_0(l)dl \end{array}\right. . \tag{18}$$

Note that $\mathcal{M}$ increases linearly with respect to N, as $N\to\infty$, and the slope represents the performance gain from collaboration. This can be validated by simulation with finite M and N, whose results are shown in Fig. 3 ($\mathcal{M}$ is shown in the vertical axis and we set $P_B(l) = 1$). We observe that the increase becomes linear when N is sufficiently large and the linearization is slower for larger α.

C. Optimization on Broadcast Probability

The broadcast probability is optimized to maximize the increasing slope of performance metric $\mathcal{M}$, defined as $\mathcal{S} = \lim_{N\to\infty}\frac{\mathcal{M}}{N}$, i.e. (note that $\mathcal{S}$ is a functional of function P_B)

$$\begin{array}{ll} & \max_{P_B} \mathcal{S}(P_B) \\ s.t. & 0 \le P_B(l) \le 1, \qquad \forall l \in \mathbb{R}, \\ & \int_{-\infty}^{\infty} lP_B(l)f_1(l)dl > 0, \\ & \int_{-\infty}^{\infty} lP_B(l)f_0(l)dl < 0. \end{array} \tag{19}$$

Note that the last two constraints mean that the average broadcasted log likelihood ratio should be larger than (smaller than) 0 if primary users emerge (have not emerged).

For an arbitrary fixed broadcast probability P_B, we perturb it by a sufficiently small δP_B. Then the perturbation on $\mathcal{S}$ is given by (the detailed calculation is omitted due to limited space)

$$\delta\mathcal{M} = \frac{\int_{-\infty}^{\infty} g(l)\delta P_B(l)dl}{(\mathcal{V}_0+\Psi)^2}, \tag{20}$$

where

$$\begin{array}{rcl} g(l) &=& (-\alpha\mathcal{P}_1\mathcal{E}_0\mathcal{E}_1 f_1(l) + \mathcal{P}_1\mathcal{E}_0 l f_1(l) - \mathcal{P}_1\mathcal{E}_1 l f_0(l)) \\ &\times& (\mathcal{V}_0+\Psi) \\ &-& \Big(f_0(l)l^2 + 2(\alpha-\alpha^2)f_0(l)\mathcal{P}_0\mathcal{E}_0^2 \\ &+& \alpha(1+\alpha-2\mathrm{p}_0\alpha)\mathcal{P}_0 f_0(l)\mathcal{E}_0^2 \\ &-& 2(1+\alpha-2\mathrm{p}_0\alpha)\mathcal{P}_0\mathcal{E}_0 l f_0(l)\Big)\mathcal{P}_1\mathcal{E}_0\mathcal{E}_1. \end{array} \tag{21}$$

Then, a necessary condition for an optimal P_B satisfies

$$\int_{-\infty}^{\infty} g(l)\delta P_B(l)dl \le 0, \qquad \forall \delta P_B. \tag{22}$$

For a fixed $P_B(l)$, we can set $\delta P_B(l)$ using the following rule to make the left hand side of (22) larger than zero if applicable (note that all the changes $\delta P_B(l)$ are sufficiently small).

Rule 1:
- When $P_B(l) \neq 1$ or 0, if $g(l) > 0$, we can set $\delta P_B(l)$ to be positive; if $g(l) < 0$, we can set $\delta P_B(l)$ to be negative.
- When $P_B(l) = 1$, if $g(l) < 0$, we can set $\delta P_B(l)$ to be negative.
- When $P_B(l) = 0$, if $g(l) > 0$, we can set $\delta P_B(l)$ to be positive.

Based on the above analysis, we obtain the following proposition which states a necessary condition for the optimal broadcast probability (the rigorous proof via variational calculus (e.g. the verification of regularity) is omitted due to limited space).

Proposition 1: The optimal broadcast probability $P_B(l)$ satisfies[10]

$$P_B(l) = \begin{cases} 0, & \text{if } g(l) < 0 \\ 1, & \text{if } g(l) > 0 \end{cases}. \quad (23)$$

A drawback of the conclusion in Prop. 1 is that it is almost impossible to obtain an explicit expression of $P_B(l)$ since the computation of $g(l)$ is coupled with the broadcast probability $P_B(l)$. The only approach to compute $P_B(l)$ is to iteratively update the values of $P_B(l)$ according to the function $g(l)$ and Rule 1 such that the metric $\mathcal{M}$ is incrementally improved. This iterative algorithm is summarized in the following table. As will be seen, the result obtained from this iterative algorithm coincides with the heuristic algorithm of threshold broadcast we will propose soon.

Algorithm 1 Procedure of Iteratively Computing the Broadcast Probability

Quantization: Discretize the real line into Q intervals for the log likelihood ratio.
Set maximum iteration times T and step function $\epsilon(t)$.
Initialize the broadcast probability $P_B(l)$.
for $t = 1 : T$ **do**
  Compute parameters $\mathcal{P}_1$, $\mathcal{P}_0$, $\mathcal{E}_1$, $\mathcal{E}_0$ and Ψ using the current $P_B(l)$.
  for $q = 1 : Q$ **do**
    Set the log likelihood ratio l as the middle point of the q-th interval.
    Compute the corresponding function $g(l)$.
    if $g(l) > 0$ **then**
      Update $P_B(l) = \min(P_B(l) + \epsilon(t), 1)$.
    end if
    if $g(l) < 0$ **then**
      Update $P_B(l) = \max(P_B(l) - \epsilon(t), 0)$.
    end if
  end for
end for

D. Threshold Broadcast

As noted before, it is prohibitively difficult to obtain an explicit expression for P_B since $g(l)$ is also dependent on P_B. However, we can discuss the following asymptotic cases:

- Large l: for H_1, when $l \to \infty$, $\frac{f_1(l)}{f_0(l)} = O(e^l)$. Therefore, $g(l)$ is dominated by $\mathcal{P}_1\mathcal{E}_0\mathcal{V}_0 f_1(l) l$, thus being positive and implying $P_B = 1$ for large l.
- Small l: when $l \to -\infty$, $g(l) \to -\infty$, which implies $P_B = 0$ for small l.
- small $|l|$: when $l = 0$, we have

$$\begin{aligned} g(0) &= -\alpha \mathcal{P}_1 \mathcal{E}_0 \mathcal{E}_1 f_1(l)(\mathcal{V}_0 + \Psi) \\ &- \mathcal{P}_1 \mathcal{P}_0 f_0(1) \mathcal{E}_0^3 \mathcal{E}_1 \left(\alpha^2 + (3 - 2\mathrm{p}_0)\alpha\right) < 0, \quad (24) \end{aligned}$$

  Therefore, $P_B(0) = 0$. Due to the continuity of g, we have $P_B(l) = 0$ when $|l|$ is sufficiently small.

Intuitively, the above conclusions mean that when the belief of the existence of primary user(s) is large (small), each secondary user should broadcast with large (small) probability. Therefore, we propose the following rule of broadcast:

$$P_B(l) = \begin{cases} 1, & \text{if } l > L_{cut} \\ 0, & \text{if } l \leq L_{cut} \end{cases}, \quad (25)$$

[10]Here we ignore the case $g(l) = 0$ which is of zero probability.

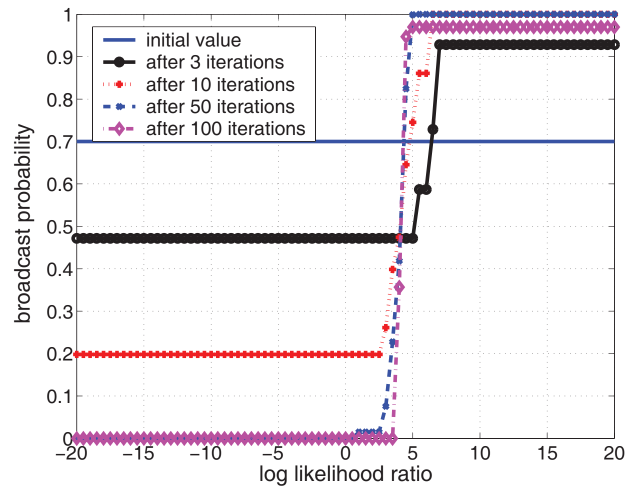

Fig. 4. Evolution of the broadcast probability in the iterative algorithm when $\alpha = 4$.

where L_{cut} is a predetermined cutoff threshold and we coin the rule as *Threshold Broadcast*.

IV. Numerical Results

In this section, we use numerical simulation to obtain the broadcast probabilities using the algorithm in Procedure 1 and to demonstrate the performance gain of threshold broadcast over the special cases of single-user spectrum sensing ($L_{cut} = \infty$) and collaborate spectrum sensing without broadcast regulation ($L_{cut} = -\infty$). Note that we omit the performance result for $\mathcal{M}$ and $\mathcal{S}$ and display only false alarm rates and detection delays, due to limited space[11].

We assume that the two distribution hypotheses H_0 and H_1 are Gaussian distributions $\mathcal{N}(1,1)$ and $\mathcal{N}(-1,1)$ (this is reasonable if the observations are sensed power in dB scale). Each statistic is obtained using 5000 realizations of the random emergence time of the primary user and noise on observations.

A. Optimal Broadcast Probability

Fig. 4 shows the evolution of broadcast probability using the algorithm in Procedure 1. Note that we set $\alpha = 4$ and carry out 100 iterations. We set $\epsilon(t) = \frac{0.1}{\sqrt{t}}$, where t is the iteration index. We observe that the probabilities at small l's are decreased to 0 and those at large l's are increased to 1 after sufficiently many iterations. An important observation is the waterfall phenomenon (at around $l = 4$) in the finally obtained broadcast probability. This justifies our proposed threshold broadcast algorithm.

Fig. 5 shows the broadcast probabilities obtained from the Procedure 1 when $\alpha = 0.5, 1, 4, 10$. We notice that, for a wide range of α, the waterfall phenomenon exists and all critical points, at which the waterfall happens, are around $l = 4$. Therefore, we can set $L_{cut} = 4$ in the threshold broadcast scheme for a wide range of α (then, we no longer need a precise value of α, which is difficult to obtain when there is little coordination in the network.). We also observe that,

[11]Moreover, the false alarm rates and detection delays are our direct concerns for the spectrum sensing.

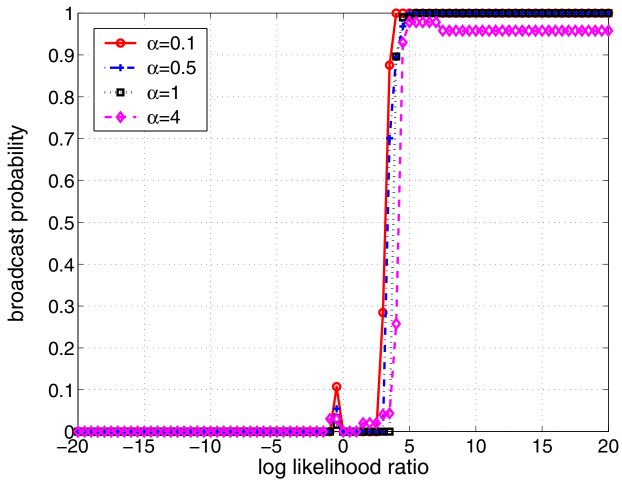

Fig. 5. Broadcast probability obtained from the iterative algorithm for differen α's.

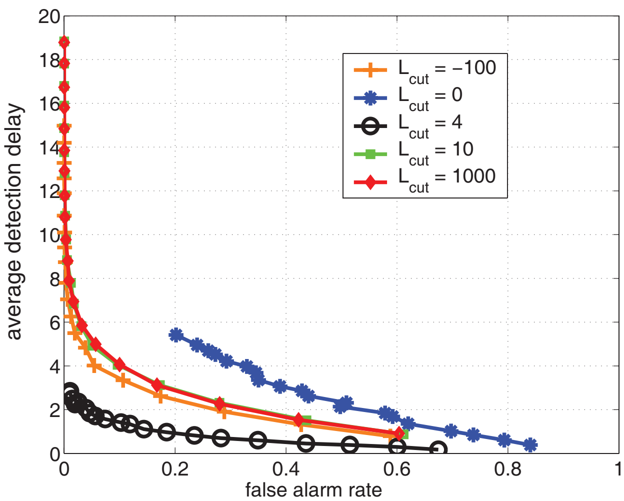

Fig. 6. ROC (average delay vs. false alarm rate) curves when $N = 20$ and $M = 5$.

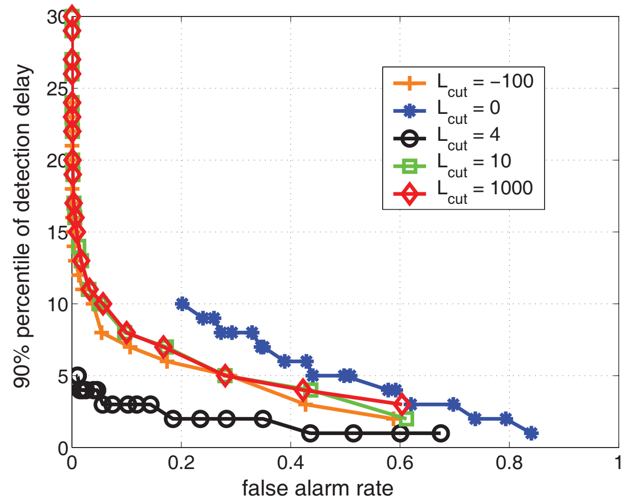

Fig. 7. ROC (90% percentile of delay vs. false alarm rate) curves when $N = 20$ and $M = 5$.

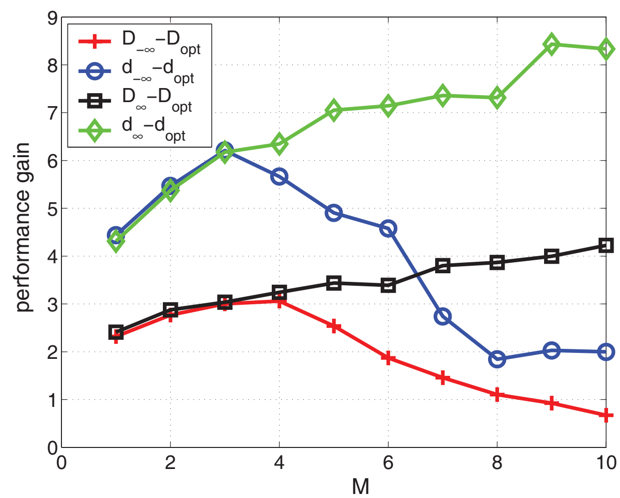

Fig. 8. Difference of average detection delays, as well as the 90% percentile detection delays.

as α increases, the critical point slightly shifts to the right. An intuitive explanation is that each secondary user should broadcast fewer packets since less resource is available (for the same number of secondary users, fewer time slots can be used). Another interesting observation is that, when α is small, the broadcast probabilities for some log likelihood ratios smaller than the critical point are also positive. However, the corresponding values are small; therefore, it does not affect the justification of the threshold broadcast scheme.

B. Threshold Broadcast

Fig. 6 shows the receiver operation characteristic (ROC) curves when $N = 20$ and $M = 5$. The performance measures are false alarm rate versus average detection delay. We tested the cases of $L_{cut} = -100$ (always broadcast without regulation), 0, 4, 10, 1000 (no broadcast; single-user spectrum sensing). It is easy to observe that, without broadcast regulation, the collaborative spectrum sensing achieves only marginally better performance than the single-user spectrum sensing. When the cutoff threshold is properly chosen (e.g. $L_{cut} = 4$), the performance can be substantially improved since collision can be considerably avoided and plenty of information can be exchanged. We also observe that the performance could be seriously impaired if the threshold is not well chosen (e.g. $L_{cut} = 0$).

Fig. 7 shows the ROC curves in which we replace the average detection delay with the 90% percentile [12] of detection delays (sorted in an ascending order) since the tail of detection delay could incur much more damage (sufficiently small detection delay can be completely tolerated by primary users). Although good average detection delay in (4) does not necessarily imply good performance of the tail of detection delay, we observe that the threshold broadcast can also substantially reduce the tail of detection delay.

Figures 8 and 9 show the performance gains (both difference and ratio) of the threshold broadcast with different M. In both figures, D_L and d_L denote the average detection delay

[12] $x\%$ percentile of a random variable is defined as $F^{-1}\left(\frac{x}{100}\right)$, where F is the cumulative distribution function of the random variable.

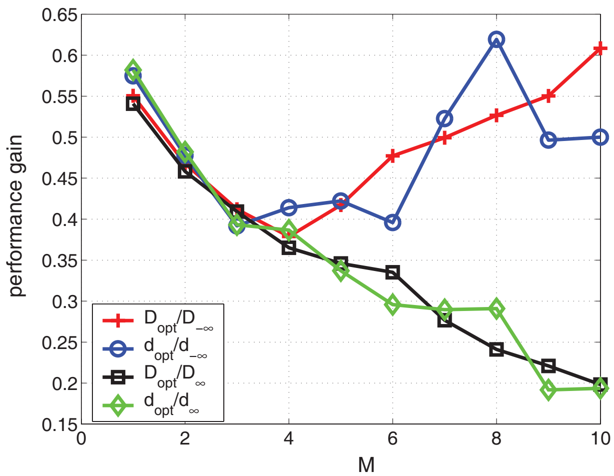

Fig. 9. Ratio of average detection delays, as well as the 90% percentile detection delays.

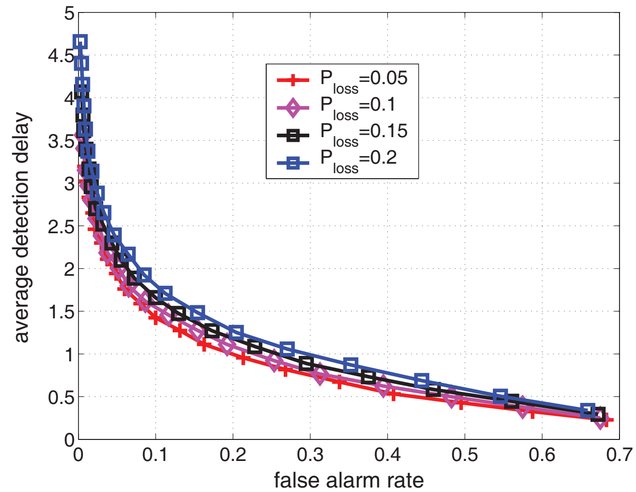

Fig. 10. ROC (average delay vs. false alarm rate) curves when $N = 20$ and $M = 5$ subject to message loss.

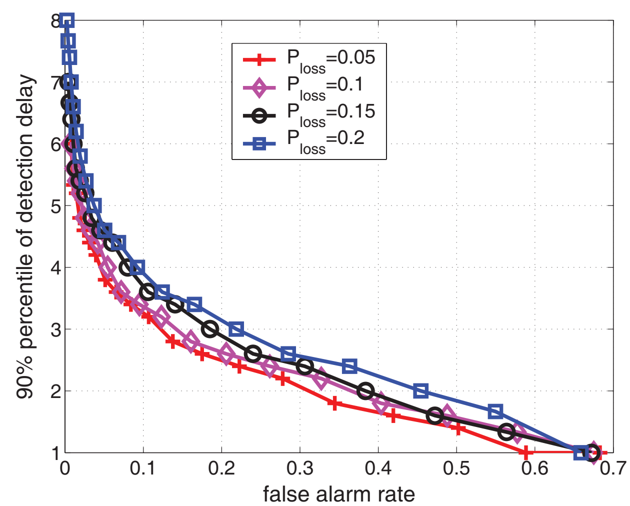

Fig. 11. ROC (90% percentile of delay vs. false alarm rate) curves when $N = 20$ and $M = 5$ subject to message loss.

and the 90% percentile of detection delay, respectively, when the broadcast threshold, L, is used. The false alarm rate is fixed at 5% by choosing a proper detection threshold γ in (1). The optimal broadcast thresholds for different M are obtained from exhaustive search and the corresponding quantities are labeled with subscript 'opt'. We observe that, averagely, the detection delay (both the average and 90% percentile) of threshold broadcast is less than 70% (or 60%) of that of broadcast without regulation (or single-user spectrum sensing). Moreover, we observe that the performance gain of threshold broadcast over the broadcast without regulation decreases as M increases (since the broadcast confliction becomes less frequent) while the performance gain over the single-user spectrum sensing increases in M (more communication time slots imply more capability of information exchange).

C. Performance with Message Loss

In our previous simulations, we did not consider the possible messages loss due to factors like fast fading, noise or interference. In Figures 10 (ROC curves with expected delay) and 11 (ROC curves with the 90 percentile of delay), we assume that each message could be lost with probability P_{loss} ranging from 0.05 to 0.2. The cutoff log likelihood is fixed at $L_{cut} = 4$. We observe that, the message loss causes only marginal performance degradation, which demonstrates the robustness of the proposed spectrum sensing scheme.

D. Performance Comparison

There are other algorithms for cooperative quickest detection. Here, we compare the performance of the proposed random broadcast based quickest spectrum sensing with that of the DualCUSUM algorithm in [2]. The details of the DualCUSUM algorithm are omitted in this paper due to limited space and can be found in [2]. For the random broadcast based approach, we fix the optimal cutoff log likelihood $L_{cut} = 4$. For the DualCUSUM algorithm, we test multiple thresholds for the individual secondary users to report their observations, which is denoted by γ_{loc}. Note that there is no collision in the DualCUSUM algorithm since a physical fusion is assumed. Moreover, we assume that there is no noise in the physical fusion, thus providing an ideal environment for the DualCUSUM algorithm. The corresponding ROC curves are shown in Fig. 12. We observe that the performances are very similar, which implies that the proposed random broadcast approach achieves similar performance to the ideal one of the DualCUSUM algorithm.

V. Conclusions

We have discussed collaborative quickest spectrum sensing via random broadcast in multiple communication channels. We assume that there is no controller or mechanism to coordinate the broadcasts, thus incurring broadcast collisions. Therefore, we consider the strategy that the probability of broadcast is a function of observed log likelihood ratios and have derived a necessary condition for the optimal function of broadcast probability. To alleviate the difficulty of computing the optimal broadcast probability, we proposed a simple scheme of threshold broadcast, in which a secondary user broadcasts only when the log likelihood ratio is larger than a certain cutoff

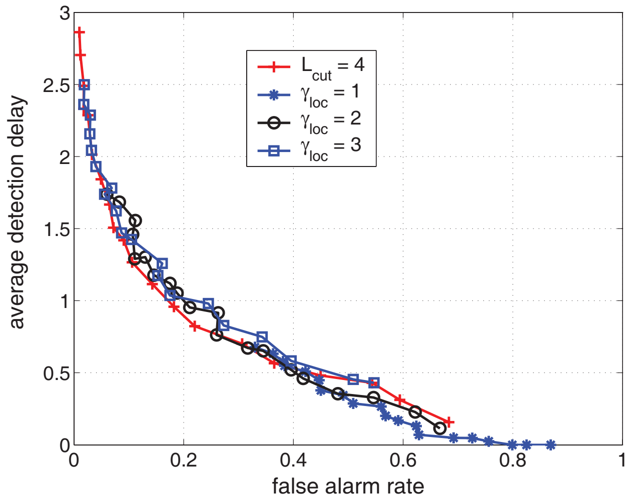

Fig. 12. Comparison between the random broadcast based quickest spectrum sensing and the DualCUSUM algorithm.

threshold. Numerical results show that this simple strategy can substantially improve the performance of spectrum sensing, compared with the strategies of random broadcast without regulation and single-user spectrum sensing.

Appendix A
Derivation of (12) and (14)

For (12), we have

$$\begin{aligned}&\frac{1}{N}E\left[\sum_{n=1}^{N} l_n I(S_n)\right]\\ =\;& \frac{1}{N}\sum_{n=1}^{N} E\left[l_n I(S_n)\right]\\ =\;& \frac{1}{N}\sum_{n=1}^{N}\int_{-\infty}^{\infty} lP_B(l)P(S_n|B_n)f_1(l)dl\\ =\;& \frac{1}{N}\sum_{n=1}^{N}\int_{-\infty}^{\infty} lP_B(l)\prod_{k=1,k\neq n}^{N}\left(1-\frac{\mathrm{p}_1}{M}\right)f_1(l)dl\\ \to\;& \exp\left(-\alpha \mathrm{p}_1\right)\int_{-\infty}^{\infty} lP_B(l)f_1(l)dl, \end{aligned} \tag{26}$$

as $M, N \to \infty$ and $\frac{N}{M} = \alpha$, where we applied $\left(1-\frac{\mathrm{p}_1}{M}\right)^N \to \exp\left(-\alpha \mathrm{p}_1\right)$. Note that $P(S_n)$, conditioned on B_n, is equal to the probability that all other secondary users do not broadcast in the same time slot, thus being equal to $\prod_{k=1,k\neq n}^{N}\left(1-\frac{\mathrm{p}_1}{M}\right)$. Therefore, I_1, normalized by N, converges to (26).

For (14), we have

$$\begin{aligned}\frac{1}{N}V_0 \;=\;& \frac{1}{N}E\left[\left(\sum_{n=1}^{N} l_n I(S_n)\right)^2\right]\\ &-\frac{1}{N}\left(E\left[\sum_{n=1}^{N} l_n I(S_n)\right]\right)^2,\end{aligned} \tag{27}$$

where the second term has been obtained in (12). Therefore, we consider only the first term, which is equal to

$$\begin{aligned}&\frac{1}{N}E\left[\left(\sum_{n=1}^{N} l_n I(S_n)\right)^2\right]\\ &=\frac{1}{N}E\left[\sum_{n=1}^{N} l_n^2 I(S_n)\right]+\frac{1}{N}E\left[\sum_{n\neq m} l_n l_m I(S_n)I(S_m)\right],\end{aligned} \tag{28}$$

which can be discussed separately. The first term is equal to

$$\begin{aligned}&\frac{1}{N}E\left[\sum_{n=1}^{N} l_n^2 I(S_n)\right]\\ =\;& \frac{1}{N}\sum_{n=1}^{N}\int_{-\infty}^{\infty} l^2P_B(l)P(S_n|B_n)f_0(l)dl\\ =\;& \frac{1}{N}\sum_{n=1}^{N}\int_{-\infty}^{\infty} l^2P_B(l)\prod_{k=1,k\neq n}^{N}\left(1-\frac{\mathrm{p}_0}{M}\right)f_0(l)dl\\ \to\;& \exp\left(-\alpha \mathrm{p}_0\right)\int_{-\infty}^{\infty} l^2P_B(l)f_0(l)dl\end{aligned} \tag{29}$$

as $M, N \to \infty$ and $\frac{N}{M} = \alpha$.

The second term is given by

$$\begin{aligned}&\frac{1}{N}E\left[\sum_{n\neq m} l_n l_m I(S_n)I(S_m)\right]\\ &=(N-1)E\left[l_1l_2I(S_1)I_(S_2)\right]\\ &=(N-1)\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} l_1l_2f_0(l_1)f_0(l_2)P_B(l_1)P_B(l_2)\\ &\times\frac{M-1}{M}\prod_{k=3}^{N}\left(1-\frac{2\mathrm{p}_0}{M}\right)dl_1dl_2\\ &=(N-1)\frac{M-1}{M}\left(1-\frac{2\mathrm{p}_0}{M}\right)^{N-2}\\ &\times\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} l_1l_2f_0(l_1)f_0(l_2)P_B(l_1)P_B(l_2)dl_1dl_2\\ &=(N-1)\frac{M-1}{M}\left(1-\frac{2\mathrm{p}_0}{M}\right)^{N-2}\left(\int_{-\infty}^{\infty} lf_0(l)P_B(l)dl\right)^2.\end{aligned} \tag{30}$$

Therefore, as $N, M \to \infty$, (27) converges to

$$\begin{aligned}&\frac{1}{N}V_0 \to\\ &\exp\left(-\alpha \mathrm{p}_0\right)\int_{-\infty}^{\infty} l^2P_B(l)f_0(l)dl\\ &+\lim_{N,M\to\infty}(N-1)\frac{M-1}{M}\left(1-\frac{2\mathrm{p}_0}{M}\right)^{N-2}\\ &\times\left(\int_{-\infty}^{\infty} lf_0(l)P_B(l)dl\right)^2\\ &-\frac{1}{N}\left(E\left[\sum_{n=1}^{N} l_n I(S_n)\right]\right)^2\\ &=\exp\left(-\alpha \mathrm{p}_0\right)\int_{-\infty}^{\infty} l^2P_B(l)f_0(l)dl\\ &+\exp\left(-\alpha \mathrm{p}_0\right)\Psi(\mathrm{p}_0,\alpha)\times\left(\int_{-\infty}^{\infty} lf_0(l)P_B(l)dl\right)^2.\end{aligned} \tag{31}$$

Now, what remains is to evaluate function $\Psi(\mathrm{p}_0, \alpha)$, which is equivalent to evaluate the following limit

$$\lim_{N,M\to\infty,N/M=\alpha} (N-1)\frac{M-1}{M}\left(1-\frac{2\mathrm{p}_0}{M}\right)^{N-2} - N\left(\left(1-\frac{\mathrm{p}_0}{M}\right)^{N-1}\right)^2. \quad (32)$$

The first term can be rewritten as

$$\begin{aligned}&(N-1)\frac{M-1}{M}\left(1-\frac{2\mathrm{p}_0}{M}\right)^{N-2}\\ =& -\frac{M-1}{M}\left(1-\frac{2\mathrm{p}_0}{M}\right)^{N-2} - \frac{N}{M}\left(1-\frac{2\mathrm{p}_0}{M}\right)^{N-2}\\ +& N\left(1-\frac{2\mathrm{p}_0}{M}\right)^{N-2}. \end{aligned}\quad (33)$$

The first two terms converges to $-\exp\left(-2\alpha\mathrm{p}_0\right)$ and $-\alpha\exp\left(-2\alpha\mathrm{p}_0\right)$, respectively, as $N, M \to \infty$. Then, we compute the difference between the third term in (33) and the second term in (32), i.e.

$$N\left(1-\frac{2\mathrm{p}_0}{M}\right)^{N-2} - N\left(\left(1-\frac{\mathrm{p}_0}{M}\right)^{N-1}\right)^2. \quad (34)$$

Let $x = \frac{1}{N}$, the limit of (34) is given by

$$\begin{aligned}&\lim_{x\to 0}\frac{1}{x}\left((1-2\alpha\mathrm{p}_0x)^{\frac{1}{x}-2} - (1-\alpha\mathrm{p}_0x)^{\frac{2}{x}-2}\right)\\ =& \frac{d}{dx}\left((1-2\alpha\mathrm{p}_0x)^{\frac{1}{x}-2} - (1-\alpha\mathrm{p}_0x)^{\frac{2}{x}-2}\right)\Big|_{x=0}\end{aligned}\quad (35)$$

Using the equality $\frac{df(x)}{dx} = f(x)g(x)$, where $g(x) = \frac{d\log f(x)}{dx}$, we have

$$\begin{aligned}&\frac{d}{dx}(1-2\alpha\mathrm{p}_0x)^{\frac{1}{x}-2}\\ =& \left(-\frac{\log(1-2\alpha\mathrm{p}_0x)}{x^2} - \frac{2\alpha\mathrm{p}_0\left(\frac{1}{x}-2\right)}{1-2\alpha\mathrm{p}_0x}\right)\\ \times& (1-2\alpha\mathrm{p}_0x)^{\frac{1}{x}-2}.\end{aligned}\quad (36)$$

It is easy to verify that

$$(1-2\alpha\mathrm{p}_0x)^{\frac{1}{x}-2} \to \exp(-2\alpha\mathrm{p}_0), \quad (37)$$

as $x \to \infty$. Hence, we only need to compute the limit of $-\frac{\log(1-2\alpha\mathrm{p}_0x)}{x^2} - \frac{2\alpha\mathrm{p}_0\left(\frac{1}{x}-2\right)}{1-2\alpha\mathrm{p}_0x}$. By applying Taylor's expansion around $x = 0$, we have

$$\begin{aligned}&-\frac{\log(1-2\alpha\mathrm{p}_0x)}{x^2} - \frac{2\alpha\mathrm{p}_0\left(\frac{1}{x}-2\right)}{1-2\alpha\mathrm{p}_0x}\\ =& -\frac{1}{x^2}\left(-2\alpha\mathrm{p}_0x - \frac{(2\alpha\mathrm{p}_0x)^2}{2} - \frac{(2\alpha\mathrm{p}_0x)^3}{3} - \ldots\right)\\ -& \frac{2\alpha\mathrm{p}_0\left(\frac{1}{x}-2\right)}{1-2\alpha\mathrm{p}_0x}\\ =& \frac{2\alpha\mathrm{p}_0}{x} + 2(\alpha\mathrm{p}_0)^2 - \frac{2\alpha\mathrm{p}}{x(1-2\alpha\mathrm{p}_0x)} + \frac{4\alpha\mathrm{p}_0}{1-2\alpha\mathrm{p}_0x} + o(x)\\ =& \frac{2\alpha\mathrm{p}_0}{x}\left(1-\frac{1}{1-2\alpha\mathrm{p}_0x}\right) + 2(\alpha\mathrm{p}_0)^2 + \frac{4\alpha\mathrm{p}_0}{1-2\alpha\mathrm{p}_0x} + o(x)\\ =& -\frac{4(\alpha\mathrm{p}_0)^2}{1-2\alpha\mathrm{p}_0x} + 2(\alpha\mathrm{p}_0)^2 + \frac{4\alpha\mathrm{p}_0}{1-2\alpha\mathrm{p}_0x} + o(x)\\ \to& -2(\alpha\mathrm{p}_0)^2 + 4\alpha\mathrm{p}_0,\end{aligned}\quad (38)$$

as $x \to 0$.

We also have

$$\begin{aligned}&\frac{d}{dx}(1-\alpha\mathrm{p}_0x)^{\frac{2}{x}-2}\\ =& \left(-\frac{2\log(1-\alpha\mathrm{p}_0x)}{x^2} - \frac{\alpha\mathrm{p}_0\left(\frac{2}{x}-2\right)}{1-\alpha\mathrm{p}_0x}\right)\\ \times& (1-\alpha\mathrm{p}_0x)^{\frac{2}{x}-2}.\end{aligned}\quad (39)$$

Again, it is easy to verify

$$(1-\alpha\mathrm{p}_0x)^{\frac{2}{x}-2} \to \exp(-2\alpha\mathrm{p}_0), \quad (40)$$

as $x \to \infty$. Hence, we only need to compute the limit of $-\frac{2\log(1-\alpha\mathrm{p}_0x)}{x^2} - \frac{\alpha\mathrm{p}_0\left(\frac{2}{x}-2\right)}{1-\alpha\mathrm{p}_0x}$. Again, by applying Taylor's expansion around $x = 0$, we have

$$\begin{aligned}&-\frac{2\log(1-\alpha\mathrm{p}_0x)}{x^2} - \frac{\alpha\mathrm{p}_0\left(\frac{2}{x}-2\right)}{1-\alpha\mathrm{p}_0x}\\ =& -\frac{2}{x^2}\left(-\alpha\mathrm{p}_0x - \frac{(\alpha\mathrm{p}_0x)^2}{2} - \frac{(\alpha\mathrm{p}_0x)^3}{3} - \ldots\right)\\ -& \frac{\alpha\mathrm{p}_0\left(\frac{2}{x}-2\right)}{1-\alpha\mathrm{p}_0x}\\ =& \frac{2\alpha\mathrm{p}_0}{x} + (\alpha\mathrm{p}_0)^2 - \frac{2\alpha\mathrm{p}}{x(1-\alpha\mathrm{p}_0x)} + \frac{2\alpha\mathrm{p}_0}{1-\alpha\mathrm{p}_0x} + o(x)\\ =& \frac{2\alpha\mathrm{p}_0}{x}\left(1-\frac{1}{1-\alpha\mathrm{p}_0x}\right) + (\alpha\mathrm{p}_0)^2 + \frac{2\alpha\mathrm{p}_0}{1-\alpha\mathrm{p}_0x} + o(x)\\ =& -\frac{2(\alpha\mathrm{p}_0)^2}{1-\alpha\mathrm{p}_0x} + (\alpha\mathrm{p}_0)^2 + \frac{2\alpha\mathrm{p}_0}{1-\alpha\mathrm{p}_0x} + o(x)\\ \to& -(\alpha\mathrm{p}_0)^2 + 2\alpha\mathrm{p}_0,\end{aligned}\quad (41)$$

as $x \to 0$.

Combining the above results, we obtain (35), which is given by

$$\begin{aligned}&\frac{d}{dx}\left((1-2\alpha\mathrm{p}_0x)^{\frac{1}{x}-2} - (1-\alpha\mathrm{p}_0x)^{\frac{2}{x}-2}\right)\Big|_{x=0}\\ =& \left(2\alpha\mathrm{p}_0 - (\alpha\mathrm{p}_0)^2\right)\exp(-2\alpha\mathrm{p}_0).\end{aligned}\quad (42)$$

This concludes the derivation.

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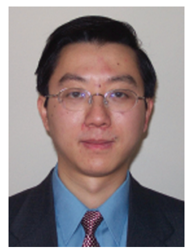

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