Joint Distributed Sensing and Channel Access in Cognitive Radio Networks

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***Abstract*—We consider a Cognitive Radio Network having one Primary User (PU) and N Secondary Users (SUs). In this paper, we study the problem of joint channel–sensing and channel–access for SUs. When the channel is in use by the PU, the signal that the PU sends and the channel fading gains are unknown to SUs. *The channel sensing problem that we consider is detecting whether or not there is an unknown signal (with random fading) in noise.* For this channel–sensing problem, we propose a sequential detection procedure based on the energy of samples that each SU observes. As soon as an SU detects the *idle/busy* state of the channel, it broadcasts it's local decision to all other SUs. We propose a global decision rule that makes a decision that the channel is *idle*, only if at least Γ out of N SUs have broadcast *idle* local decisions; otherwise, the global decision rule makes a decision that the channel is *busy*. Also, the channel access is provided to the SU that is the first one to broadcast an *idle* decision. We study the detection and false–alarm performance of our proposed procedure, and compare the performance with that of Sequential Probability Ratio Test (SPRT) based sensing procedure. From the Receiver Operating Characteristic (ROC), and the average sample number (ASN) metrics, we observe that our energy based sequential sensing procedure yields a better probability of detection than the SPRT based procedure for a given probability of false–alarm. Also, as the threshold on the number of *idle* local decisions Γ increases, probability of detection also increases, but at the cost of detection delay.**

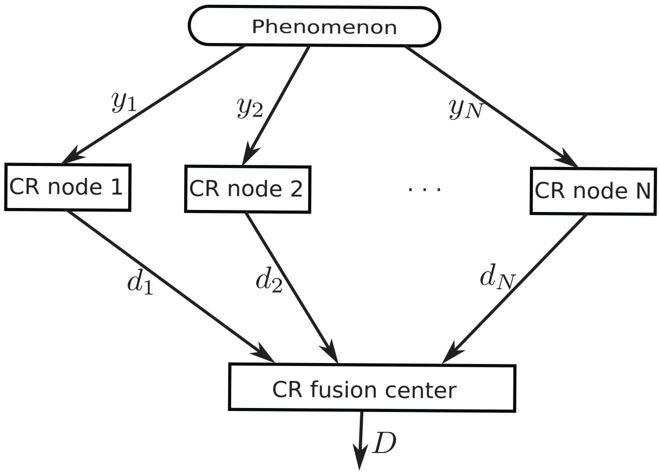

Fig. 1. An illustration of spectrum sensing. In this setting, during each time–slot, each SU, or Cognitive Radio (CR) s, observes y_s, and makes a local decision d_s. The global decision is made based on all local decisions. A global decision about the *idle/busy* state of the channel can be made either by fusion center (as shown in the Figure), or can be done without a fusion center (as in distributed sensing). In distributed sensing, the local decisions are broadcast by each SU to all other SUs, and hence, the global decision is made by each SU (in the same manner as is done by the fusion center).

I. Introduction

The ever increasing demand for high data rate necessitates the study of Cognitive Radio Networks (CRNs) where the unlicensed users, called Secondary Users (SUs), sense and access a channel primarily allocated for Primary (or licensed) Users (PUs). A channel that is currently not in use by a PU can be used by an SU for improving the spectrum utilisation. Also, an SU can not access a channel which is in use by a PU. Thus, there is a need to study dynamic spectrum sensing and allocation of spectrum among different SUs. In this paper, we propose a distributed joint channel sensing and access among competing SUs.

A. Previous Work

In [1], a parallel–fusion network architecture is proposed for decentralized detection (see Fig. 1). This paper also considers an unknown deterministic signal corrupted by Gaussian noise. This paper, however, uses cyclic–feature detection techniques for signal detection.

In [2], the authors consider a distributed spectrum sensing problem among competing SUs. In this model, the *idle/busy* state of the channel is observed directly without any errors, and the authors propose a sensing policy based on Partially Observable Markov Decision Process (POMDP). However, in practice, obtaining the channel state without errors is impossible, and any detection problem suffers from type I and type II errors.

In [3], the authors pose the problem of spectrum sensing and access, again, in the POMDP framework. The problem was posed as one of a finite time horizon; however, in this work also, there has not been any mention of a practical detection algorithm that takes into account of false alarm and mis–detection probabilities.

The survey paper by Axell et al. (see [4]) describes many methods used for signal detection in CRs. All the detectors studied in [4] are fixed sample size detectors available in literature such as Energy Detector (ED) [5], Cyclo stationary

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detection, Feature detection etc. ED works closer to the optimal detector [4] when it has perfect knowledge of probability density functions (PDF) in the presence and absence of the primary user. However, ED requires more number of samples (i.e. sensing time) to detect low signal–to–noise ratio [6] primary signal. The fundamental limits for sensing is studied by Tandra and Sahai, [6].

A sequential detector has been proposed by Wald called Sequential Probability Ratio Test (SPRT) [7], which takes samples sequentially, computes Log–Likelihood Ratio (LLR), and compares LLR with upper (or lower) thresholds for a binary hypothesis testing problem. If LLR falls in between two thresholds, the detector proceeds to take next sample. This process is continued until the detector makes a decision. The number of samples it requires is random, and in general, the expected number of samples required for making a decision is finite.

The expected number of samples in Wald's SPRT may not be acceptable for many applications, and hence, Xin et al. ([8], [9]) have proposed truncated sequential tests, where the SU stops sensing once it reaches the maximum number of samples. Thereafter, [8], [9] compares the cumulative LLR with a threshold to make the *idle/busy* decision about the primary channel. This algorithm is called Sequential Shift Chi Square test (SSCT), and this reduces the average number of samples with comparable detection performance.

In [10], the authors extended the SSCT for the case of multiple SUs, and proved that more energy can be saved by censoring. Here, cooperative spectrum sensing is carried out in which all the SUs computes the cumulative LLR locally, and compares it with some thresholds. The local decision (0 or 1) is sent to the Fusion Center(FC). The FC employs either OR rule, or AND rule to make a global decision. Here, authors minimize the maximum average energy required per SU.

In [9] and [10], energy of a sample follows the chi–square distribution. Also, in both the models authors assume that the channel gain is known at the SU which may not be possible in practice. In [10], FC stops receiving the decisions from SUs when it receives 1 or 0. This may lead to poor detection performance. Also, AND and OR rules are not necessarily throughput optimum.

B. Contributions of the Paper

We summarise the essential contributions of this paper below.

- Almost all the work reported so far considers the case of detecting whether the channel carries a known signal or not. In this work, we consider a practical setting in which the detection problem is whether or not there is an unknown signal in noise.
- We also consider the case of wireless channels that undergo fading (fading is neglected in many of the works cited above). Each SU sees an independent fading channel.
- We propose a distributed sequential sensing and access procedure for SUs. The local decision rule at a SU is based on the observations of the SU. The local decision is one of *idle*, *busy*, or *take the next sample*. If the local decision is *idle* or *busy*, the SU stops sensing further in the time–slot, and broadcasts its local decision to all SUs. The global decision is declare that the channel is *idle* if at least Γ SUs report *idle* state.
- Once the global decision is made, and if it is *idle*, the channel access is provided to the SU that first made the local decision *idle*. The reason for this is that the channel conditions are better for the SU that reported the local decision first. Thus, arbitration among competing SUs is done in a fair manner, and the collisions, if any, among the SUs are avoided.

C. Organization of the paper

The rest of the paper is organised as follows. In Section II, we describe the System model. In Section III, we describe the problem statement which includes a detection procedure and a global decision rule for distributed spectrum sensing. In section IV, we discuss the simulation results and the inference from the results. Conclusions and future work are discussed in section V.

II. System Model

In this Section, we describe the CRN, the communication model of PU, and the sensing model of the SUs.

We consider a discrete–time CRN comprising one channel, and hence, one Primary User (PU) and a set of N Secondary Users (SUs) denoted by $\mathcal{S} = \{1, 2, 3, \cdots, N\}$. The channel is intended for use by the PU, and when it is not in use by the PU, it can be used by any of the SUs. Time is slotted, and the length of time–slots is considered to be unity. Thus, we measure time–slots in non–negative integers $\{1, 2, 3, \cdots\}$.

We assume the following model of traffic of the PU. In each time–slot k, the PU uses the channel with probability $\lambda \in (0, 1)$, and is idle with probability $1 - \lambda$. We assume that the traffic of PU in each time–slot is independent of everything else. Thus, the random process that models the channel utilization by the PU is an i.i.d. Bernoulli(λ) process.

We assume that the PU uses BPSK modulation scheme (BPSK is chosen for convenience, and the work described here can easily be adapted for any other modulation scheme). Thus, when the PU uses the channel, the signal that is sent by the PU is a vector of symbols, where each symbol is either $-\sqrt{E}$ or $\sqrt{E}$ (recall that E is the symbol energy). If the PU uses the channel during time–slot k, the ith symbol transmitted in time–slot k is given by $X[k, i] \in \{-\sqrt{E}, \sqrt{E}\}$. We note that $X[k, i]$ takes each of the values $-\sqrt{E}$ and $\sqrt{E}$ with probability 0.5.

During each time–slot k, the channel that each SU $s \in \mathcal{S}$ sees is an independent Rayleigh fading channel with fading gain $H_s[k]$, i.e., for each SU s, the fading process $\{H_s[k], k \in \{1, 2, 3, \cdots\}\}$ is i.i.d. Rayleigh distributed with $\mathbb{E}H_s^2[k] = 1$.

In each time–slot k, each SU s samples the channel sequentially (i.e., one at a time), and obtains the samples

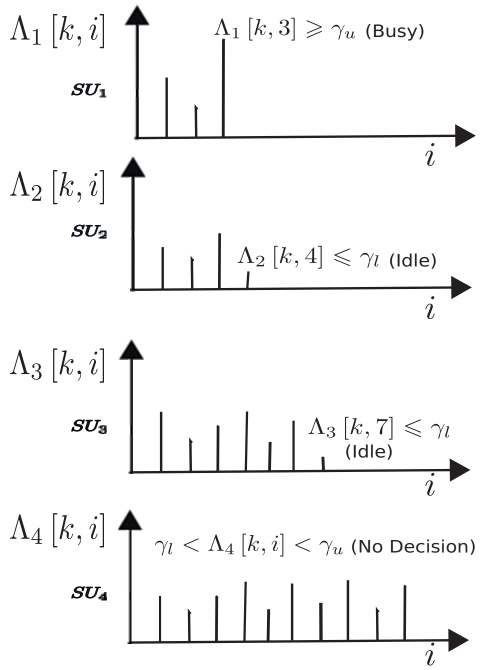

Fig. 2. An illustration of the sequential sensing procedure with four SUs, for a given time–slot k. X axis is labelled the sample indices 1, 2, 3, $\cdots$, 10. SU_1 would broadcast a local decision 1 (busy) at sampling instant 3, SU_2 would broadcast a local decision 0 (idle) at sampling instant 4, SU_3 would broadcast a local decision 0 (idle) at sampling instant 7, and SU_4 would not make any decision, as all $\Lambda_4[k,i] \in (\lambda_l, \lambda_u)$. Here, the global decision is always 0 (idle). *If $\Gamma = 2$, then a global decision of 0 (idle) is made at sampling instant 7, and the access is given to SU_2.*

$Y_s[k,1], Y_s[k,2], Y_s[k,3], \cdots$. Thus, if the PU uses the channel during time–slot k, each SU s receives

$$Y_s[k,i] = H_s[k]X[k,i] + Z_s[k,i], \quad (1)$$

where $Z_s[k,i]$s are i.i.d. Gaussian random variables having the distribution $\mathcal{N}(0, N_0/2)$ (recall that N_0 is the noise power spectral density). Note that when the channel is not in use by the PU, $X[k,i] = 0$, and hence, $Y_s[k,i]$s are Gaussian noise samples.

III. Joint Sensing and Channel Access Problem

In this Section, we pose the joint sensing and channel access problem in CRNs.

During each time–slot k, each SU s observes the samples $Y_s[k,1], Y_s[k,2], \cdots$ sequentially up to a maximum of M samples. The problem is to detect whether, at the beginning of time–slot k, the channel is in *idle* state, or *busy* state from the sequence of samples $Y_s[k,1], Y_s[k,2], \cdots, Y_s[k,M]$ of all SUs.

The ith observation in time–slot k of SU s follows one of the two hypotheses. For each time–slot k,

$$\mathbf{H_0}: \quad Y_s[k,i] = Z_s[k,i], \; i = 1,2,\cdots,M \quad (2)$$

$$\mathbf{H_1}: \quad Y_s[k,i] = H_s[k]X_s[k,i] + Z_s[k,i], \; i = 1,2,\cdots,M. \quad (3)$$

Define the energy of each sample $Y_s[k,i]$ as

$$\chi_s[k,i] = Y_s[k,i]^2 \quad (4)$$

We make an approximation here. Under hypothesis $\mathbf{H_0}$, the energy of each sample follows a Gaussian distribution, i.e., $\chi_s[k,i] \sim \mathcal{N}(\mu_0, \sigma_0^2)$, and under hypothesis $\mathbf{H_1}$, the energy $\chi_s[k,i] \sim \mathcal{N}(\mu_1, \sigma_1^2)$. Since energy takes only non–negative values, the approximation can be made more tight by keeping a very low probability mass to the Gaussian tail that takes negative values (this is possible by appropriately choosing the parameters E, μ and σ). All the previous work on energy–based detection uses a chi–squared distribution for $Y_s[k,1]^2 + Y_s[k,2]^2 + \cdots + Y_s[k,i]^2$. This, however, does not work in our problem, as the term $H_s[k]X_s[k,i]$ *in* $\mathbf{H_1}$ *itself is a random variable, and hence,* $\chi_s[k,i]$ *does not follow a noncentral chi–squared distribution*.

Let $f_0(\cdot)$ and $f_1(\cdot)$ be the probability density functions (pdfs) corresponding to the distributions $\mathcal{N}(\mu_0, \sigma_0^2)$ and $\mathcal{N}(\mu_1, \sigma_1^2)$, respectively. The parameters (mean μ_0 and variance σ_0^2) of the pdf f_0, and the parameters (mean μ_1 and variance σ_1^2) of the pdf f_1 are obtained in Appendix A.

At the beginning of each time–slot k, each SU s after having observed $Y_s[k,i]$ and obtained $\chi_s[k,i]$, computes the likelihood ratio of energy samples observed in time–slot k as follows.

$$L_s[k,i] = \frac{\prod_{m=1}^{i} \frac{1}{\sqrt{2\pi\sigma_1^2}} \exp\left(\frac{-(\chi_s[k,m]-\mu_1)^2}{2\sigma_1^2}\right)}{\prod_{m=1}^{i} \frac{1}{\sqrt{2\pi\sigma_0^2}} \exp\left(\frac{-(\chi_s[k,m]-\mu_0)^2}{2\sigma_0^2}\right)}. \quad (5)$$

From $L_s[k,i]$, by taking natural logarithm, we obtain LLR of $\chi_s[k,i]$s until ith sample as,

$$\begin{aligned} &\Lambda_s[k,i] \\ &= \ln L_s[k,i] \\ &= i \ln\left(\frac{\sigma_0}{\sigma_1}\right) + \sum_{m=1}^{i}\left[\frac{(\chi_s[k,m]-\mu_0)^2}{2\sigma_0^2} - \frac{(\chi_s[k,m]-\mu_1)^2}{2\sigma_1^2}\right] \\ &= \Lambda_s[k,i-1] + \ln\left(\frac{\sigma_0}{\sigma_1}\right) + \left[\frac{(\chi_s[k,i]-\mu_0)^2}{2\sigma_0^2} - \frac{(\chi_s[k,i]-\mu_1)^2}{2\sigma_1^2}\right]. \end{aligned} \quad (6)$$

Each SU s sequentially computes, $\Lambda_s[k,1], \Lambda_s[k,2], \cdots$ until it crosses either a lower threshold γ_l, or an upper threshold γ_u. Thus, the local decision of SU s after having observed ith sample in time–slot k is given by

$$D_s[k,i] = \begin{cases} 0, & \text{if } \Lambda_s[k,i] \leqslant \gamma_l, \\ 1, & \text{if } \Lambda_s[k,i] \geqslant \gamma_u, \\ \text{take next sample}, & \text{otherwise.} \end{cases} \quad (7)$$

If $D_s[k,i] = 0$ or 1, the SU s stops sensing, and broadcasts its local decision $D_s[k,i]$ to all other SUs. If the number of samples reaches M, and if for all $i = 1,2,\cdots,M$, $\Lambda_s[k,i] \in (\gamma_l, \gamma_u)$, then the sensing procedure is stopped.

A. Global Decision Rule

At the beginning of each time–slot k, each SU s observes the broadcast messages (local decisions) from other SUs. Let $G[k,i]$ be the global decision that is made after an SU observes ith sample (during time–slot k).

$$G[k,i] = \begin{cases} 0, & \text{if at least } \Gamma \text{ SUs report a local decision of 0,} \\ 1, & \text{otherwise.} \end{cases} \tag{8}$$

If $G[k,i] = 0$, the channel access is given to the SU s that is the first SU to broadcast $D_s[k,i] = 0$; in case of a tie between many SUs for channel access, the tie is broken arbitrarily.

See Fig. 2 for an illustration of the sensing and channel access procedure described.

IV. Results and Discussion

In this Section, we evaluate the detection and the false alarm performance of the distributed sequential procedure for a CRN having 1 PU and $N = 10$ SUs. During any time–slot, the PU uses the slot with probability $\lambda = 0.2$. The sequential detection is done up to a maximum of $M = 10$ samples per time–slot. The BPSK constellation taken is $\{-1, 1\}$, and thus $E = 1$.

We choose the following values for the global threshold Γ, 1, 2, and 5. For each of the global threshold Γ, we run the experiment for 10^6 time–slots, and obtain the probability of detection and the probability of false alarm. We plot the results in Fig. 3, which shows the Receiver Operating Characteristic (ROC) curve of the proposed detection procedure for various values of Γ.

From Fig. 3, we observe that as as the global threshold Γ increases, the probability of detection increases (for the same probability of false alarm). Also, the procedure described in this paper is compared with a simple Log–likelihood based detector (called LD) with M samples. It is evident from Fig. 3 that our procedure based on energy (called ED) performs better than that of LD for each Γ, i.e., for a given probability of false alarm, probability of detection of our procedure (ED) is larger than that of LD.

The average sensing delay is computed for our procedure (ED), for each of the global threshold values $\Gamma = 1, 2$, and 5. Average detection delay is plotted as a function of probability of false alarm in Fig. 4. From Fig. 4, we observe that as Γ increases, the detection delay decreases. This is because, for a large Γ, it takes many SUs to report a local decision of 0 (idle). Since, more SUs require more time to report 0, the average sensing delay increases with Γ.

Also, we study the conditional delay defined as the average number of samples taken to make a global decision of 0, when the channel is actually *idle*. The conditional delay for the proposed ED procedure is plotted as a function of probability of false alarm, and is plotted in Fig. 5.

From Fig. 5, we observe that the conditional delay increases with Γ for the reason that it takes more SUs (and hence, more time) for large Γ to cross the global threshold Γ. Also, we observe that in many iterations, it takes 1 or 2 samples to cross the threshold.

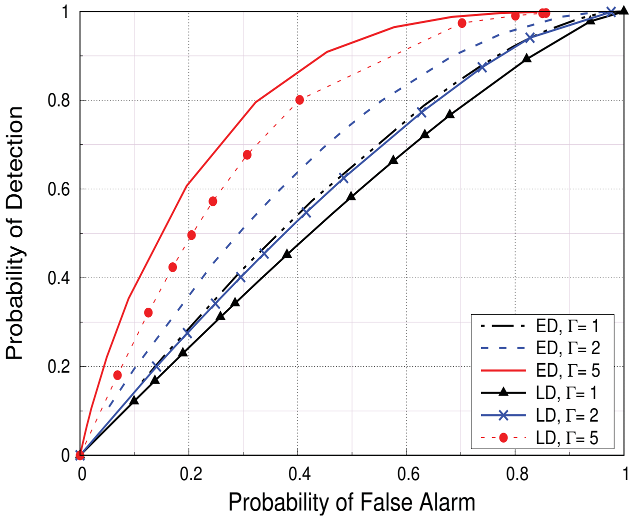

Fig. 3. Receiver Operating Characteristic (ROC) of the proposed sequential procedure based on Energy Detector (ED) is compared with that of a Log–likelihood based Detector (LD). The procedures are evaluated for a global decision rule having a threshold of $\Gamma = 1, 2$, and 5.

V. Conclusions

In this paper, we have proposed a joint distributed spectrum sensing and channel access procedure in a CRN. Our spectrum sensing is based on sequentially checking whether the average energy of samples collected thus far in the current time–slot has exceeded a threshold. Our sensing procedure is based on two thresholds, a lower one γ_l and an upper one γ_u. If $\Lambda_s[k,i]$ crosses a threshold, a local decision is made and is broadcast to all SUs. A global decision rule makes a global decisions when the number of local decisions is more than a global threshold. We have also proposed a channel access policy which favours the SU that sees the best channel. We observe that as the global threshold Γ increases, the probability of detection increases, thereby increasing the quality of the detection procedure. We have compared our procedure with a simple Log–likelihood based procedure, and shown that our procedure is better in terms of probability of detection for a given probability of false alarm.

Our future work lies in obtaining analytical expressions for the lower and upper thresholds γ_l and γ_u as a function of various parameters like probability of false alarm.

Appendix A
The Model Parameters $\mu_0, \sigma_0, \mu_1, \sigma_1$

Recall that μ_0 is the mean of $\chi_s[k,i]$ under hypothesis $\mathbf{H_0}$. By definition,

$$\mu_0 = \mathbb{E}[\chi_s[k,i] \mid \mathbf{H} = \mathbf{H_0}].$$

Since $\chi_s[k,i] = Y_s^2[k,i]$, we have

$$\mu_0 = \mathbb{E}[Y_s^2[k,i] \mid \mathbf{H} = \mathbf{H_0}].$$

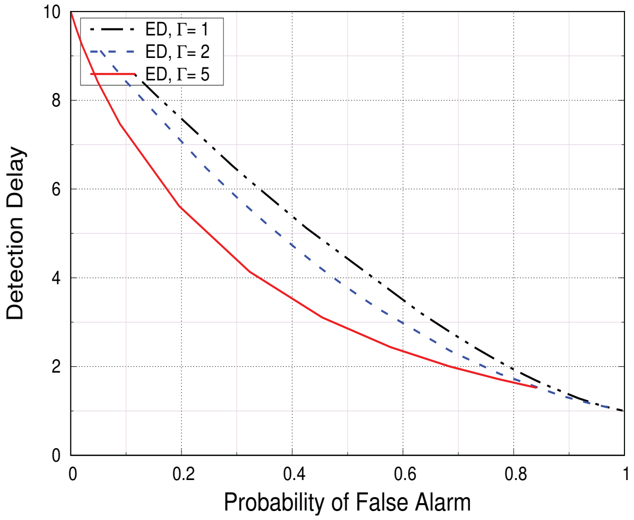

Fig. 4. The delay performance of proposed sequential detection procedure for various Γ is plotted against the probability of false alarm. Here $N = 10$, $\lambda = 0.2$, $M = 10$.

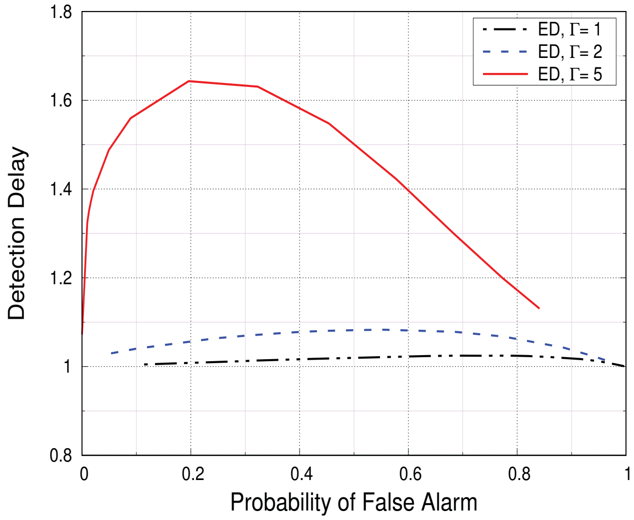

Fig. 5. The conditional delay (delay of *idle* decisions when the channel is actually *idle*) performance of proposed sequential detection procedure for various Γ is plotted against the probability of false alarm. Here, $N = 10$, $\lambda = 0.2$, $M = 10$. Note that in most of the cases, a global decision is made within a delay of 1 or 2 samples.

From Eqn. (2), we see that $Y_s[k,i] = Z_s[k,i]$, and also $\mathbb{E}[Z_s^2[k,i]] = \sigma^2$. Hence,

$$\mu_0 = \mathbb{E}[Y_s^2[k,i] \mid \mathbf{H} = \mathbf{H_0}] = \sigma^2.$$

Recall that σ_0^2 is the variance of $\chi_s[k,i]$ under hypothesis $\mathbf{H_0}$. Hence,

$$\begin{aligned}\sigma_0^2 &= \text{Var}(\chi_s[k,i] \mid \mathbf{H} = \mathbf{H_0}) \\ &= \mathbb{E}[\chi_s^2[k,i] \mid \mathbf{H} = \mathbf{H_0}] - (\mathbb{E}[\chi_s[k,i] \mid \mathbf{H} = \mathbf{H_0}])^2 \\ &= \mathbb{E}[Y_s^4[k,i] \mid \mathbf{H} = \mathbf{H_0}] - \left(\mathbb{E}[Y_s^2[k,i] \mid \mathbf{H} = \mathbf{H_0}]\right)^2 \\ &= \mathbb{E}[Z_s^4[k,i]] - \left(\mathbb{E}[Z_s^2[k,i]]\right)^2 \\ &= 3\sigma^4 - \sigma^4 \\ \sigma_0^2 &= 2\sigma^4.\end{aligned}$$

Recall that μ_1 is the mean of $\chi_s[k,i]$ under hypothesis $\mathbf{H_1}$. By definition,

$$\begin{aligned}\mu_1 &= \mathbb{E}[\chi_s[k,i] \mid \mathbf{H} = \mathbf{H_1}] \\ &= \mathbb{E}[Y_s^2[k,i] \mid \mathbf{H} = \mathbf{H_1}] \\ \mu_1 &= \mathbb{E}[(H_s[k,i]X_s[k,i] + Z_s[k,i])^2]\end{aligned}$$

We note that $H_s[k,i]$, $X_s[k,i]$, and $Z_s[k,i]$ are all independent of each other, and hence,

$$\mu_1 = \mathbb{E}[H_s^2[k,i]]\mathbb{E}[X_s^2[k,i]] + \sigma^2$$

Since, the symbol transmitted by PU is either $\sqrt{E}$, or $-\sqrt{E}$ (recall that we assumed a BPSK transmitter), $\mathbb{E}[X_s^2[k,i]] = E$. Also, since, $H_s[k,i]$ is Rayleigh distributed with $\mathbb{E}[H_s^2[k,i]] = 1$, we have

$$\mu_1 = E + \sigma^2.$$

Also, recall that σ_1^2 is the variance of $\chi_s[k,i]$ under hypothesis $\mathbf{H_1}$. Thus, we have

$$\begin{aligned}\sigma_1^2 &= \text{Var}(\chi_s[k,i] \mid \mathbf{H} = \mathbf{H_1}) \\ &= \mathbb{E}[\chi_s^2[k,i] \mid \mathbf{H} = \mathbf{H_1}] - (\mathbb{E}[\chi_s[k,i] \mid \mathbf{H} = \mathbf{H_1}])^2 \\ &= \mathbb{E}[Y_s^4[k,i] \mid \mathbf{H} = \mathbf{H_1}] - \left(\mathbb{E}[Y_s^2[k,i] \mid \mathbf{H} = \mathbf{H_1}]\right)^2 \\ &= \mathbb{E}[(H_s[k,i]X_s[k,i] + Z_s[k,i])^4] - \left(\mathbb{E}[(X_s[k,i]H_s[k,i] + Z_s[k,i])^2]\right)^2\end{aligned}$$

Note that

$$\begin{aligned}&\mathbb{E}[(H_s[k,i]X_s[k,i] + Z_s[k,i])^4] \\ &= \mathbb{E}\left[H_s^4[k,i]X_s^4[k,i] + 4H_s^3[k,i]X_s^3[k,i]Z_s[k,i]\right] \\ &\quad + \mathbb{E}\left[6H_s^2[k,i]X_s^2[k,i]Z_s^2[k,i] + 4H_s[k,i]X_s[k,i]Z_s^3[k,i] + Z_s^4[k,i]\right] \\ &= \mathbb{E}[H_s^4[k,i]]\mathbb{E}[X_s^4[k,i]] + 6E\sigma^2 + \mathbb{E}[Z_s^4[k,i]] \\ &= 2E^2 + 6E\sigma^2 + 3\sigma^4,\end{aligned}$$

and hence,

$$\begin{aligned}\sigma_1^2 &= 2E^2 + 6E\sigma^2 + 3\sigma^4 - \mu_1^2 \\ &= 2E^2 + 6E\sigma^2 + 3\sigma^4 - \left(E + \sigma^2\right)^2 \\ &= E^2 + 4E\sigma^2 + 2\sigma^4.\end{aligned}$$

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