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***Abstract*—In cognitive radio networks, secondary users (SUs) utilize the unused spectrum slots in the assigned band for the primary users (PUs). Conventional cognitive radio networks operate in half-duplex (HD) mode. Recently, full-duplex (FD) communication has become feasible. SUs with full-duplex capabilities can sense the spectrum and transmit simultaneously, which improves the efficiency of cognitive radio networks. In this paper, we study the performance of spectrum sensing based on general likelihood ratio (GLR) when the SU is operating in FD mode. We compare our results to the HD GLR case. We present the effect of residual self interference on the performance of the spectrum sensing technique. Moreover, we consider uncertainty in estimating the variance of the combined residual self interference and noise and show its effect on the performance of the FD GLR.**

***Index Terms*—Full-Duplex, Spectrum sensing, Cognitive Radio, Cognitive radio network, Quickest detection, GLR**

I. Introduction

Conventionally, radios operate in half-duplex (HD) mode, i.e., either transmit or receive at the frequency at the same time. Recently, simultaneous transmit and receive by a wireless device on the same frequency band, i.e., operate in full-duplex (FD) mode, has become possible. Self interference cancellation is the key for a practical FD communication [1]. Therefore, most of the current research in FD communication is directed towards designing efficient self interference cancellation techniques. However, residual self interference is inevitable and developing algorithms adaptable to it remains a challenging issue in FD communication.

Rapid deployment of wireless communication systems in diverse applications resulting in an increasing urge for designated exclusive bandwidth allocations [2] is challenged by the scarcity of dedicated spectrum resources. Recent statistical studies of dedicated spectrum usage revealed spectrum under utilization, which triggered the interest in cognitive radio networks based on deploying dynamic spectrum allocation to achieve higher spectrum utilization [3]. In cognitive radio networks, a secondary user (SU) accesses the spectrum whenever the spectrum owner, named primary user (PU), is not transmitting or both PU and SU share the spectrum under the PU's defined terms of usage. Consequently, reliable spectrum sensing is paramount to realization of efficient and successful cognitive radio networks.

Efficient utilization of spectrum holes in PU's assigned band calls for robust spectrum sensing techniques at the SU's radio. Amongst the class of signal detection that is used to decide between two hypotheses is general likelihood ratio (GLR) [4], which is used when detection is performed with some unknown parameters. GLR has been adopted in many signal detection frameworks including spectrum sensing [5]. All the GLR based approaches presented in [6], [7], [8] are based on evaluating the sample covariance matrix and its eigenvalue decomposition, which has high implementation complexity.

Currently, cognitive radio networks are assumed to operate in HD mode. If the SUs can operate in FD mode, i.e., sense and transmit at the same time, the spectrum usage efficiency will be improved significantly. Existing literature on FD spectrum sensing is still limited. However, recently the broader subject of FD cognitive radio networks has attracted an increasing attention from the research community. Examples of FD spectrum sensing can be found in [9], [10], [11]. The authors studied the performance of FD spectrum sensing using energy detection in [9], using correlator detector in [10] and in the context of collaborative sensing in [11]. In the aforementioned papers, the probability of detection was affected by the residual self interference when compared to the HD case.

Our contributions in this work as compared to existing literature are as follows. We study the performance of spectrum sensing based on GLR when the SU is equipped with full-duplex capabilities. Residual self interference is considered in our system model and the distributions of the two hypotheses are adjusted accordingly. In addition, uncertainty in estimating the variance of the combined residual self interference signal and noise is considered and its effect on the performance of the sensing efficiency is presented. We compare our results to the HD case and show the degradation in the performance of FD GLR due to residual self interference as well as variance uncertainty.

The rest of this paper is organized as follows. In Section II we present our system model. Spectrum sensing based on GLR for HD system is then reviewed in Section III. In Section IV, we present our analysis on spectrum sensing in FD system under residual self interference. Results are then presented in Section VI. The paper is then concluded in Section VII.

II. System Model

In HD system, as each SU is listening to a specific frequency band, it starts collecting samples, $y_{HD}[i]$. Hypothesis H_0

denotes the case when the PU is not using this frequency band, i.e., empty spectrum slot. Hypothesis H_1 denotes the case when the PU is using this frequency band. The received signal is given by:

$$\begin{aligned} H_0 &: y_{HD}[i] = w[i], \qquad i = 1, ..., N \\ H_1 &: y_{HD}[i] = x[i] + w[i], \quad i = 1, .., N \end{aligned} \tag{1}$$

where $w[i]$ is white Gaussian noise with variance σ_w^2, $x[i] = hs[i]$ is the product of the channel gain h and the PU's signal $s[i]$ and N is the total number of samples. σ_w^2 is receiver dependant and can be estimated on average ahead of time. $x[i]$ is assumed to be Gaussian with zero mean and variance σ_x^2 [5]. The value of σ_x^2 depends on the channel gain and the power of the PU signal. When the PU signal is present, $y_{HD}[i]$ follows $\mathcal{N}(0, \sigma_w^2 + \sigma_x^2)$, which we denote by F_1^{HD}. When there exists an empty spectrum slot, $y_{HD}[i]$ follows $\mathcal{N}(0, \sigma_w^2)$, which we denote by F_0^{HD}. The HD signal to noise ratio is $\gamma_{HD} = \sigma_x^2/\sigma_w^2$.

In FD system, as depicted in Fig. 1, the SU transmits its own signal while simultaneously sensing the spectrum. Although self interference passes through two cancellation steps, one in the radio frequency (RF) domain and the second in the baseband domain, residual self interference is unavoidable. The residual self interference, $z[i]$, is modelled as Gaussian with zero mean and variance $\sigma_z^2 = \gamma_{zw}\sigma_w^2$ [9], [10], [11], where γ_{zw} is the residual self interference signal to noise ratio. The received signal in the FD case is given by:

$$\begin{aligned} H_0 &: y_{FD}[i] = z[i] + w[i], \qquad i = 1, ..., N \\ H_1 &: y_{FD}[i] = x[i] + z[i] + w[i], \quad i = 1, .., N. \end{aligned} \tag{2}$$

When the PU signal is present, $y_{FD}[i]$ follows $\mathcal{N}(0, \gamma_{zw}(\sigma_w^2 + 1) + \sigma_x^2)$, which we denote by F_1^{FD}. When there exists an empty spectrum slot, $y_{FD}[i]$ follows $\mathcal{N}(0, \sigma_w^2(\gamma_{zw}+1))$, which we denote by F_0^{FD}. The FD signal to noise ratio is given by $\gamma_{FD} = \gamma_{HD}/(1 + \gamma_{zw})$.

We follow the generalized likelihood ratio change detection algorithm [5] to decide on the presence or absence of the PU signal. The scenario we are interested in is when σ_w^2 is known on average and σ_x^2 is within a range $\sigma_{\text{S}x}^2 \le \sigma_x^2 \le \sigma_{\text{M}x}^2$. The decision statistic is computed sequentially for a given N and compared to a threshold to decide on the status of the spectrum. We are interested in the case where the spectrum is empty and we are detecting the entrance of the PU. After the entrance of the PU signal, the decision statistic will start to show a consistent positive drift. We start by reviewing the GLR for HD system and then proceed to present our analysis for the FD system.

III. Spectrum Sensing Based on GLR in HD System

For the detection of the entrance of the PU signal, the collected samples by the SU first follow distribution F_0^{HD} with density function f_0^{HD}. As a PU starts using the spectrum, the distribution changes to F_1^{HD} with density f_1^{HD}. We summarize the work presented in [5], which is based on the

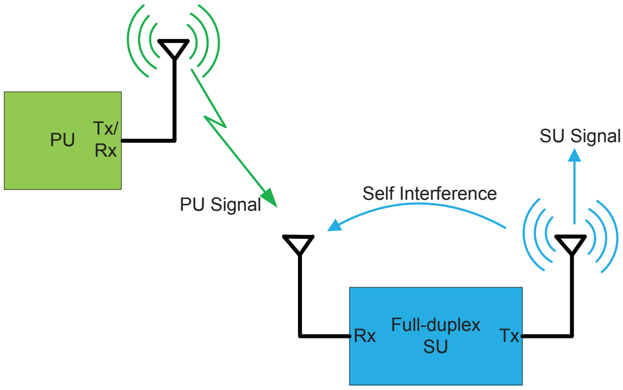

Fig. 1. SU equipped with full-duplex capabilities transmitting its own signal while listening for the PU signal.

GLR analysis [12], [13] below. The log-likelihood ratio for a known σ_x^2 is estimated for each sample sequentially as:

$$l_1(y_{HD}[i]) = \ln\left\{\frac{f_1^{HD}(y_{HD}[i])}{f_0^{HD}(y_{HD}[i])}\right\}. \tag{3}$$

By substituting the probability density functions f_1^{HD} and f_0^{HD} and taking the natural log, (3) reduces to:

$$l_1(y_{HD}[i]) = \frac{1}{2}\ln\left\{\frac{\sigma_w^2}{\sigma_x^2+\sigma_w^2}\right\} + \frac{\sigma_x^2 y^2[i]}{2(\sigma_x^2+\sigma_w^2)\sigma_w^2}. \tag{4}$$

During H_0 [5]

$$\begin{aligned} \mathbb{E}_{f_0^{HD}}\left\{l_1\left(y_{HD}[i]\right)\right\} &= \int f_0^{HD}(y_{HD}) \ln\left\{\frac{f_1^{HD}(y_{HD})}{f_0^{HD}(y_{HD})}\right\} dy \\ &= -D\left(f_0^{HD}||f_1^{HD}\right) \le 0, \end{aligned} \tag{5}$$

and during H_1 [5]

$$\begin{aligned} \mathbb{E}_{f_1^{HD}}\left\{l_1\left(y_{HD}[i]\right)\right\} &= \int f_1^{HD}(y_{HD}) \ln\left\{\frac{f_1^{HD}(y_{HD})}{f_0^{HD}(y_{HD})}\right\} dy \\ &= D\left(f_1^{HD}||f_0^{HD}\right) \ge 0, \end{aligned} \tag{6}$$

where $\mathbb{E}\{\cdot\}$ denotes the expectation operation, $D\left(f_0^{HD}||f_1^{HD}\right)$ is the Kullback-Leibler divergence of f_0^{HD} from f_1^{HD} and $D\left(f_1^{HD}||f_0^{HD}\right)$ is the divergence of f_1^{HD} from f_0^{HD}. Therefore, $l_1(y_{HD})$ exhibits a negative drift during H_0 and a positive drift during H_1. We denote the decision statistic for the detection of the entrance of the PU's signal by B_N, which is estimated as [5]:

$$\begin{aligned} B_N &= \max_{k\le N} \sup_{\sigma_x^2} \ln\left\{\prod_{i=k+1}^{N} \frac{f_{1,\sigma_x^2}^{HD}(y_{HD}[i])}{f_0^{HD}(y_{HD}[i])}\right\}, \\ &= \max_{k\le N} \sup_{\sigma_x^2} \sum_{i=k+1}^{N} \left(\frac{1}{2}\ln\left\{\frac{\sigma_w^2}{\sigma_x^2+\sigma_w^2}\right\}\right. \\ &\quad + \left.\frac{\sigma_x^2 y_{HD}^2[i]}{2(\sigma_x^2+\sigma_w^2)\sigma_w^2}\right). \end{aligned} \tag{7}$$

Within the above expression, $f_{1,\sigma_x^2}^{HD}$ is the probability density function of the received HD signal with the actual variance of the PU's signal being σ_x^2 and k is the sample at which the decision statistic, B_N, started to show a consistent positive drift.

IV. Spectrum Sensing Based on GLR in FD System

Due to residual self interference in FD systems, the log-likelihood ratio for the detection of the entrance of the PU signal is estimated for each sample sequentially as:

$$l_2(y_{FD}[i]) = \ln\left\{\frac{f_1^{FD}(y[i])}{f_0^{FD}(y[i])}\right\}. \tag{8}$$

By substituting the probability density functions f_1^{FD} and f_0^{FD} and taking the natural log, (8) reduces to:

$$\begin{aligned} l_2(y_{FD}[i]) &= \frac{1}{2}\ln\left\{\frac{\sigma_w^2(\gamma_{zw}+1)}{\sigma_x^2+\sigma_w^2(\gamma_{zw}+1)}\right\} \\ &+ \frac{\sigma_x^2 y_{FD}^2[i]}{2(\sigma_x^2+\sigma_w^2(\gamma_{zw}+1))\sigma_w^2(\gamma_{zw}+1)}. \end{aligned} \tag{9}$$

While the spectrum is empty, i.e., H_0

$$\begin{aligned} \mathbb{E}_{f_0^{FD}}\{l_2(y_{FD}[i])\} &= \int f_0^{FD}(y_{FD})\ln\left\{\frac{f_1^{FD}(y_{FD})}{f_0^{FD}(y_{FD})}\right\}dy \\ &= -D\left(f_0^{FD}||f_1^{FD}\right) \le 0, \end{aligned} \tag{10}$$

where the Kullback-Leibler divergence of f_0^{FD} from f_1^{FD}, $D\left(f_0^{FD}||f_1^{FD}\right)$, estimated as

$$\begin{aligned} D\left(f_0^{FD}||f_1^{FD}\right) &= -\frac{1}{2}\ln\left\{\frac{\sigma_w^2(\gamma_{zw}+1)}{\sigma_x^2+\sigma_w^2(\gamma_{zw}+1)}\right\} \\ &- \frac{\sigma_x^2}{2\left(\sigma_x^2+\sigma_w^2(\gamma_{zw}+1)\right)}. \end{aligned} \tag{11}$$

After the entrance of the PU in the case H_1,

$$\begin{aligned} \mathbb{E}_{f_1^{FD}}\{l_2(y_{FD}[i])\} &= \int f_1^{FD}(y_{FD})\ln\left\{\frac{f_1^{FD}(y_{FD})}{f_0^{FD}(y_{FD})}\right\}dy \\ &= D\left(f_1^{FD}||f_0^{FD}\right) \ge 0, \end{aligned} \tag{12}$$

where $D\left(f_1^{FD}||f_0^{FD}\right)$ estimated as:

$$\begin{aligned} D\left(f_1^{FD}||f_0^{FD}\right) &= \frac{1}{2}\ln\left\{\frac{\sigma_w^2(\gamma_{zw}+1)}{\sigma_x^2+\sigma_w^2(\gamma_{zw}+1)}\right\} \\ &+ \frac{\sigma_x^2}{2\sigma_w^2(\gamma_{zw}+1)}. \end{aligned} \tag{13}$$

$l_1(y_{FD})$ shows a negative drift during H_0 and a positive drift during H_1. The decision statistic based on GLR for the FD system, E_N, can be written as:

$$\begin{aligned} E_N &= \max_{k\le N}\sup_{\sigma_x^2}\left\{\sum_{i=k+1}^{N} l_{2,\sigma_x^2}(y_{FD}[i])\right\}, \\ &= \max_{k\le N}\sup_{\sigma_x^2}\ln\left\{\prod_{i=k+1}^{N}\frac{f_{1,\sigma_x^2}^{FD}(y_{FD}[i])}{f_0^{FD}(y_{FD}[i])}\right\}, \\ &= \max_{k\le N}\sup_{\sigma_x^2}\sum_{i=k+1}^{N}\left(\frac{1}{2}\ln\left\{\frac{\sigma_w^2(\gamma_{zw}+1)}{\sigma_x^2+\sigma_w^2(\gamma_{zw}+1)}\right\}\right. \\ &+ \left.\frac{\sigma_x^2 y_{FD}^2[i]}{2(\sigma_x^2+\sigma_w^2(\gamma_{zw}+1))\sigma_w^2(\gamma_{zw}+1)}\right). \end{aligned} \tag{14}$$

Let:

$$\begin{aligned} f_1^{FD}(\sigma_x^2) &= \frac{N-k}{2}\ln\left\{\frac{\sigma_w^2(\gamma_{zw}+1)}{\sigma_x^2+\sigma_w^2(\gamma_{zw}+1)}\right\} \\ &+ \frac{\sigma_x^2\widehat{y}_{FD}}{2(\sigma_x^2+\sigma_w^2(\gamma_{zw}+1))\sigma_w^2(\gamma_{zw}+1)}. \end{aligned} \tag{15}$$

where $\widehat{y}_{FD} = \sum_{i=1}^{N} y_{FD}^2[i]$. σ_x^2 is not known, we find its estimate σ_x^{2*} by solving (15) for the value that maximizes it within the given range $\sigma_{Sx}^2 \le \sigma_x^2 \le \sigma_{Mx}^2$, which results in (16). So, in order to estimate the decision statistic E_N, we first find σ_x^{2*} through (16) and then substitute it in (14) for a preset N and iterative k.

The decision statistic E_N is computed for the entire N samples and then compared to a threshold λ_E to decide on the presence or absence of the PU's signal according to:

$$E_N \underset{H_0}{\overset{H_1}{\gtrless}} \lambda_E. \tag{17}$$

The relationship between the average delay to false alarm, $\overline{T_0}$, and the threshold, h, is obtained through [12], [13]:

$$\lambda_E = -\ln\{a/b\}, \tag{18}$$

where a is a design parameter, which is set based on $\overline{T}_0$ according to:

$$\overline{T}_0 \ge 1/a, \tag{19}$$

and b is given by:

$$b = 3\ln\left\{a^{-1}\left(1+\frac{1}{D_E(f_{1,\sigma_{Sx}^2}^{FD}||f_0^{FD})}\right)^2\right\}, \tag{20}$$

where $D_E(f_{1,\sigma_{Sx}^2}^{FD}||f_0^{FD})$ is estimated as in (13) at σ_{Sx}^2. When detecting an empty spectrum slot, the probability of false alarm is defined as:

$$P_f = Pr\left(E_N > \lambda_E|H_1\right), \tag{21}$$

and the probability of detection as:

$$P_d = Pr\left(E_N > \lambda_E|H_1\right). \tag{22}$$

V. Uncertainty in Estimating the Variance of Residual self Interference and Noise

In Section IV, perfect knowledge of the noise variance as well as the variance of the residual self interference was assumed. However, in practical systems, due to several reasons including lack of noise calibration and interference, noise uncertainty is inevitable. In addition, error in estimating the variance of the residual self interference is likely due to calibration and/or the self interference channel not being a flat fading channel. This affects the sensitivity of the GLR algorithm presented above.

In the next Section, We study the sensitivity of the GLR algorithm in the FD case, when there is uncertainty in the noise variance and/or the residual self interference. It is worth noting that this is different from the case where the variance is completely unknown, which leads to nonparametric detection

$$\sigma_x^{2*} = \begin{cases} \sigma^2_{\mathrm{M}x}, & (N-k) \leq \frac{\widehat{y}_{FD}}{\sigma^2_{\mathrm{M}x}+\sigma^2_w(\gamma_{zw}+1)}, \\ \frac{\widehat{y}_{FD}}{N-k} - \sigma^2_w\left(\gamma_{zw}+1\right), & \frac{\widehat{y}_{FD}}{\sigma^2_{\mathrm{M}x}+\sigma^2_w(\gamma_{zw}+1)} \leq (N-k) \leq \frac{\widehat{y}_{FD}}{\sigma^2_{\mathrm{S}x}+\sigma^2_w(\gamma_{zw}+1)}, \\ \sigma^2_{\mathrm{S}x}, & (N-k) \geq \frac{\widehat{y}_{FD}}{\sigma^2_{\mathrm{S}x}+\sigma^2_w(\gamma_{zw}+1)}. \end{cases} \quad (16)$$

as in [14]. Uncertainty in the noise variance and/or the residual self interference leads to leads to what is known as signal to noise ratio (SNR) wall, which is the SNR level below which reliable sensing is impossible [15]. Below the SNR wall, increasing the number of collected samples does not improve the performance of the sensing algorithm. In order to estimate the SNR wall for the FD GLR algorithm presented above, we model both uncertainty by the parameter $\rho > 1$, which quantifies the size of uncertainty. The variance of $(z[i] + w[i])$ lies in the range $\left(\sigma_z^2 + \sigma_w^2\right) \in \left[(1/\rho)\left(\sigma_z^2+\sigma_w^2\right) : \rho\left(\sigma_z^2+\sigma_w^2\right)\right]$. $\rho = 1$ indicates that there exists no uncertainty in the variance of $(z[i] + w[i])$.

VI. Results

In this section, we simulate the performance of the GLR FD algorithm presented above. We use the HD case as a baseline against which we compare the performance of the FD case. We start by plotting the decision statistic for the GLR algorithm and proceed to present the probability of detection versus the required number of samples at a fixed probability of false alarm. We then study the effect of uncertainty in the noise and residual self interference variance on the performance of the GLR FD algorithm. Typically, the requirement for an efficient spectrum sensing is to achieve $P_d \geq 90\%$, while $P_f \leq 10\%$. The results below are for a fixed $P_f = 10\%$, $\sigma^2_{\mathrm{S}x} = 0.5\sigma^2_{\mathrm{S}x}$ and $\sigma^2_{\mathrm{M}x} = 2\sigma^2_{\mathrm{S}x}$.

A. *GLR decision statistic*

We start by plotting the decision statistic for both HD and FD GLR algorithms in Fig. 2. The simulation is for 400 samples with the PU entering the spectrum at the 100^{th} sample. $\gamma_{HD} = 10$ dB and $\gamma_{zw} = 3$ dB. The FD GLR algorithm is simulated at $\rho = 1$, i.e., perfect knowledge of the variance of the noise and the residual self interference, and at $\rho = 2$. As a PU enters the spectrum, the decision statistic in the three cases starts to increase rapidly. However, the amplitude of the HD case is higher than the two FD cases, which indicates that once a threshold is set, detection of the PU signal will have a higher probability of detection at lower number of collected samples.

B. *Probability of detection vs. number of samples*

We numerically compute the probability of detection for HD GLR and FD GLR ($\rho = 1$ and $\rho = 2$) algorithms at a fixed probability of false alarm for different number of samples collected after the entrance of the PU signal. Fig. 3 shows the simulation results for P_d vs. number of samples, where γ_{zw} was fixed at 6 dB, while γ_{HD} changed from (a) 3 dB, to (b) 6 dB to (c) 10 dB. The same simulation parameters are used

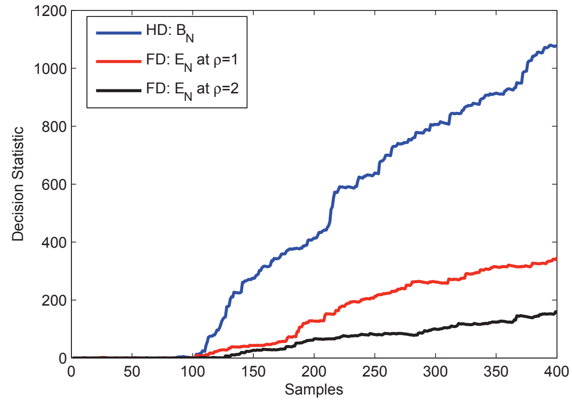

Fig. 2. Decision statistic for the HD case, FD at $\rho = 1$ and FD at $\rho = 2$. The PU enter the spectrum at the 100^{th} sample.

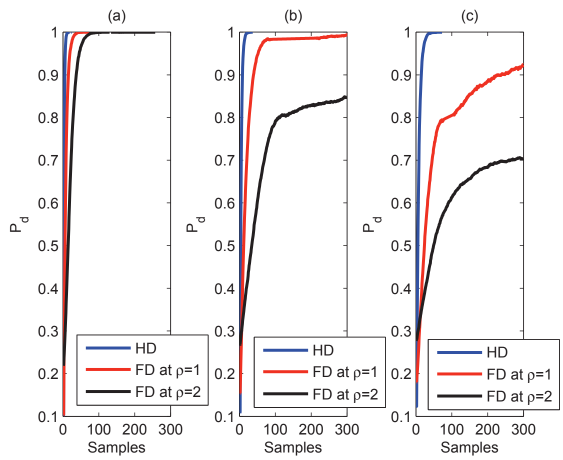

Fig. 3. Probability of detection vs. number of samples for $\gamma_{zw} = 6$ dB and (a) $\gamma_{HD} = 10$ dB, (b) $\gamma_{HD} = 6$ dB and (c) $\gamma_{HD} = 3$ dB.

in Fig. 4, but for $\gamma_{HD} = 9$ dB and (a) $\gamma_{zw} = 9$ dB, (b) $\gamma_{zw} = 12$ dB and (c) $\gamma_{zw} = 15$ dB. It can be inferred from both figures that HD GLR algorithm performs better than FD GLR algorithm. This degradation in the performance of the FD GLR algorithm is due to the residual self interference. As γ_{HD} increases, lower number of samples are required to achieve the target $P_d \geq 90\%$. For example, for $\gamma_{zw} = 6$ dB and $\gamma_{HD} = 3$ dB, HD GLR requires approximately 10 samples, FD GLR at $\rho = 1$ requires approximately 275 samples, while FD GLR at $\rho = 2$ fails to achieve $P_d > 70\%$ for a preset number of collected samples of 300. Same notion is inferred as γ_{zw}

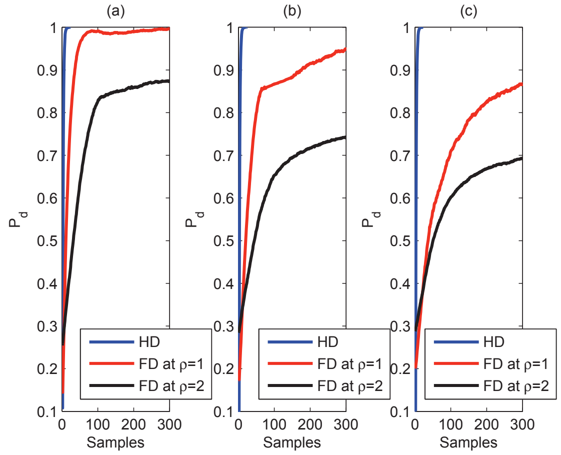

Fig. 4. Probability of detection vs. number of samples for $\gamma_{HD} = 9$ dB and (a) $\gamma_{zw} = 9$ dB, (b) $\gamma_{zw} = 12$ dB and (c) $\gamma_{zw} = 15$ dB.

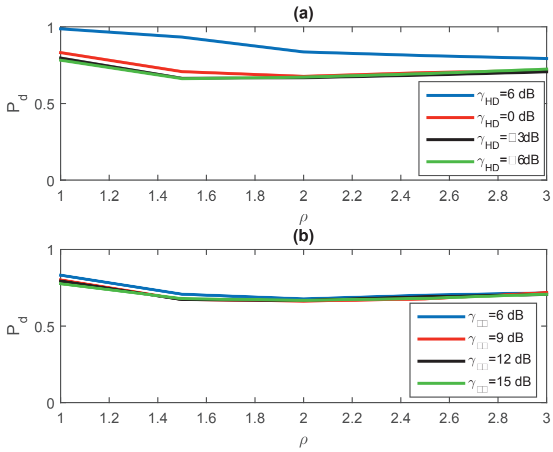

Fig. 5. Probability of detection vs. ρ using 250 samples (a) $\gamma_{zw} = 6$ dB and different γ_{HD}, (b) $\gamma_{HD} = 0$ dB and different γ_{zw}.

decreases.

C. Uncertainty in the variance of the noise and residual self interference

We first introduce different levels of uncertainty and study its performance on the FD GLR algorithm. In Fig. 5, we plot P_d vs. ρ at (a) fixed γ_{zw} and different γ_{HD} and (b) fixed γ_{HD} and different γ_{zw}. Regardless of the level of γ_{zw} and γ_{HD}, the degradation in the performance of the FD GLR saturates at $\rho \geq 2$. We then use $\rho = 2$ in Fig. 6 to evaluate the boundaries, i.e., the SNR wall of the FD GLR algorithm. We plot P_d vs a large number of samples (1000) for (a) different levels of $(\gamma_{zw} - \gamma_{HD})$ and for (b) low γ_{HD} levels. If γ_{zw} is approximately 9 dB higher than γ_{HD}, or more, P_d saturates at 70%, no matter how many samples are collected. In addition, for $\gamma_{HD} \leq -9$ dB, P_d also saturates to 70%, no matter how low γ_{zw} gets.

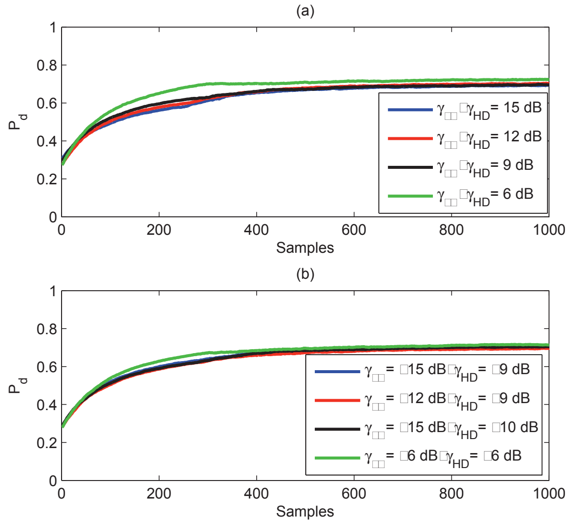

Fig. 6. Probability of detection vs. number of samples (a) different levels of $(\gamma_{zw} - \gamma_{HD})$ values (b) low γ_{HD} levels.

VII. Conclusion

Due to the scarcity of the spectrum, efficient utilization of it is imperative in any cognitive radio network. FD secondary users can transmit and sense at the same time, which improves the efficiency of exploiting empty spectrum slots. In this paper, we presented FD GLR algorithm with residual self interference taken into consideration. We compared the performance of FD GLR to HD GLR. In addition, we introduced uncertainty in the estimation of the variance of noise and residual self interference, an we evaluates its impact on the performance of FD GLR algorithm. Moreover, we investigated the performance of the presented FD GLR in some extreme cases.

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