Sequential Detection based Cooperative Spectrum Sensing Algorithms in Cognitive Radio

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Abstract— **This paper considers the problem of Spectrum Sensing in Cognitive Radio Networks. For this we use a recently developed distributed cooperative algorithm DualCUSUM. The algorithm is based on sequential change detection techniques which optimally use the past observations. But DualCUSUM requires the knowledge of the channel gains for each of the secondary users. In this work we modify DualCUSUM to develop GLR-CUSUM which can work with imprecise estimates of the channel gains. Next we extend the algorithm to the case where the receiver noise power is also not known exactly. We show that the SNR wall problem encountered in this scenario is not experienced by our algorithm.**

Keywords-Cognitive Radio, Cooperative Spectrum Sensing, Decentralized Sequential Detection, Robust Detection.

I. INTRODUCTION

Cognitive Radios use the radio spectrum owned by other users. They perform radio environment analysis, identify the spectral holes and then operate in those holes ([6], [9], [16]). In cognitive radio terminology *Primary user* refers to a user who is allocated the rights to use the spectrum. *Secondary user* refers to the users who try to use the frequency bands allocated to the primary user when the primary user is not using it.

Spectrum Sensing, an essential component of the Cognitive Radio technology involves, 1) identifying spectrum holes (white space) and 2) when an identified spectrum hole is being used by the secondary users, to quickly detect the onset of primary transmission. This needs to be done such that the guaranteed interference levels to the primary are maintained and there is efficient use of spectrum by the secondary. This involves detecting reliably, quickly and robustly, possibly weak, primary user signals. For example the IEEE 802.22 standard ([6]) requires a sensitivity of -116dBm.

For cognitive radios two typical scenarios have been identified. One is to use the white space in the TV broadcast channels ([9], [21]). In this case one often knows the timings when different TV broadcast channels are ON. A cognitive radio can use the channels which are free. During the time of broadcast at a channel also, a TV band can be used by cognitive users at locations where its transmission is weak, i.e., it cannot be used by a TV receiver at that place. For this a cognitive radio has to detect a spectral hole in space. If the cognitive radio is mobile then this can lead to detection of spectral hole in time also. In another scenario several IEEE 802.11 and Bluetooth devices may be sharing the ISM band (2.5 GHz). A device may use a channel when others are not using. This leads to detecting a white space in time where the channel may be available for use for a few msecs or secs ([8]).

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The channel from the primary transmitter to a secondary user can be bad because of shadowing and time varying multipath fading. To alleviate this problem, Cooperative Spectrum Sensing ([4], [7], [12], [26]) is envisaged, whereby the spatial diversity inherent in radio environment is leveraged by allowing multiple secondary users to cooperate. This reduces the average time to detect the primary user. This in turn lowers the interference to the primary user (when it switches ON), while increasing the spectrum usage of the secondary (when the primary switches OFF).

Another important problem in spectrum sensing is the impact of modeling uncertainties, e.g., the noise distribution, noise power and/or channel gain may not be exactly known ([21]). Because cognitive radios have to detect primary signals at very low SNR, these modeling uncertainties can cause an SNR wall, a level below which spectrum sensing fails to be robust to modeling uncertainties. More recently it is shown in [15] that if the primary user goes ON and OFF at different times one may be able to detect this change in a reliable and robust manner and then SNR wall can be breached. Of course in this case one is looking for spectral holes in time.

In this paper we provide a spectrum sensing algorithm (for detecting spectral holes in time) which can be used cooperatively by multiple cognitive users distributed in space. It is robust to the channel gain and noise power uncertainties. In the next section we describe briefly different Spectrum Sensing algorithms available in the literature.

A. *Literature Survey*

For spectrum sensing, primarily three signal processing techniques ([4]) are proposed in literature: Matched filter [18], Energy Detection [18] and cyclo-stationary feature detection [27]. Matched filtering is optimal but requires detailed knowledge of primary signaling. When no such knowledge is available an Energy Detector is optimal ([18]). Hence most of the literature is based on energy detection.

Cooperative spectrum sensing where the decisions of different secondaries are fused to obtain the final decision has been studied in [7], [17], and [26].

Almost all of the above studies detect the spectrum hole from a single snapshot of observations from one or more nodes. In [20] we have applied a decentralized cooperative algorithm, DualCUSUM, developed in [1], for spectrum sensing. It performs better than many other algorithms developed recently. This algorithm is based on Sequential Detection techniques, in particular on CUSUM [14]. DualCUSUM can be implemented online, is iterative in nature and requires minimal computations at each step.

More recently sequential detection techniques have been used in [10] and [13] also. The algorithms in [10] and [13] are designed for a single node (thus have no cooperative features). The algorithm in [13] is tested for detecting a sinusoidal signal in white noise while [10] studies various sequential change detection algorithms when there is uncertainty in parameters and uses rank statistics.

B. Our Contribution

The algorithm in [20] requires the exact knowledge of the channel gains and noise power for each of the secondary user. In this paper we extend the algorithm in [20] to GLR-CUSUM which does not assume the precise knowledge of channel gains and noise power. In this algorithm instead of CUSUM, GLR ([11]) is used at the local nodes, which also has some optimality properties. We will show that our algorithm performs better than the algorithms in [10] and [15].

The paper is organized as follows. Section II describes our model. In Section III we present the DualCUSUM algorithm and then modify it to GLR-CUSUM and MGLR-CUSUM which can tolerate uncertainties in transmit power, fading gain and receiver noise power. We conclude this section by comparing the performance of the various algorithms. Section IV concludes the paper.

II. MODEL

Consider a Cognitive Radio System with L secondary users who sense a channel via Energy Detectors. The observations made on the channel by these users are processed and sent to a fusion center which makes a decision whether the channel is free or not. Then that decision is sent to all secondary users for possible use of channel.

The secondary nodes have to detect the change in the status of the channel in two situations. First, when the primary has been using the channel and it stops transmission. A short detection delay here will allow increased spectrum utilization opportunities for the secondary user. The second situation is when the channel has been free and the secondaries are using the channel. They need to sense the channel to see if the primary starts transmission. This is possible under the assumption that in between their transmissions, secondaries stop intermittently and sense the channel to see if the primary has started transmission. If yes the secondaries need to stop using that channel. A small detection delay here will cause minimal interference to the primary users. This setup can be used in the in-band spectrum sensing in IEEE 802.22.

We present our algorithm in the setup of the second scenario {primary OFF→ON} but the same algorithm works under the first scenario as well. In Section III we will provide details and also an example.

We consider a slotted system. During the OFF period of the primary, in the beginning of each slot, the secondaries only sense the channel and make observations. Based on those observations they transmit some data to the fusion center for making the final decision. If the fusion center decides that the channel is free, then the secondaries will use the rest of the slot for data transmission.

Let at random time T the primary starts transmission. Then in the k^{th} slot the signal received by the l^{th} secondary is,

$$X_{k,l} = N_{k,l}, \qquad k = 1, 2, ..., T-1,$$
$$X_{k,l} = h_l S_k + N_{k,l}, \quad k = T, T+1, ...$$

where h_l is the channel gain of the l^{th} user, S_k is the primary user signal and $N_{k,l}$ is observation noise at the l^{th} user. It is assumed that the fading is constant during the interval of the observation (say approximately for duration of an ON/OFF period). Slow fading scenarios with primary staying ON and OFF for a few seconds will approximately satisfy this. This assumption is commonly made in literature ([10], [12]). We also assume that $\{S_k, k \geq 1\}$ and $\{N_k\}$ are independent and identically distributed (i.i.d.) sequences independent of each other and T.

There are commonly two possible hypotheses about the pre and post change distribution of $X_{k,l}$. Some studies ([17], [22]) assume the pre-change distribution as $N(\mu_0, \sigma_l^2)$ and post-change $N(\mu_0 + P_l, \sigma_l^2)$, i.e., the presence of primary is modeled as a change in mean of Gaussian noise, where $N(a,b)$ denotes Gaussian distribution with mean a and variance b. In the other model post change distribution is $N(\mu_0, \sigma_l^2 + P_l)$ i.e. presence of primary is modeled as an increase in variance ([18]). In this paper we provide algorithms for the variance change model. Although we present our algorithms in this setup, our algorithms are general and can be applied to other models as well (in particular to the mean change case).

The aim is to detect the change (at random time T) at the fusion center as soon as possible at a time τ ($\geq T$) using the messages transmitted from the L sensors with an upper bound on probability of false alarm (see below for precise statement). For this each of the L nodes uses its observation $X_{k,l}$ to generate a signal $Y_{k,l}$ and transmits to the Fusion Center. The data received at the fusion center is corrupted by the i.i.d. receiver noise Z_k at the fusion center. The fusion center uses the observations $Y_{k,1}, Y_{k,2}, ..., Y_{k,L}$ to decide between the two hypotheses H_0 (the primary is not transmitting) and H_1 (the primary is transmitting). If H_0 is chosen the secondaries continue to use the channel in slot k and the spectrum sensing session continues. If H_1 is detected, the secondaries typically switch over to an alternate channel. To transmit $Y_{k,1}, Y_{k,2}, ..., Y_{k,L}$ from the L secondaries to their fusion node, they need a Multiple Access Channel (MAC) protocol. Time Division Multiple Access (TDMA) is the most commonly used protocol. We will allow all nodes to transmit simultaneously and use physical layer fusion. This saves time in transmission.

We develop a robust cooperative algorithm for spectrum sensing in this setup. Let $P_{FA} = P(\tau < T)$ be the probability that the fusion center decides that the primary has started transmitting while it has not. We state the goal of the problem as:

$$\min EDD \triangleq E[(\tau - T)^+],$$
$$subject\ to\ P_{FA} = P(\tau < T) \leq \alpha \qquad (1)$$

where EDD denotes the Expected Detection delay i.e., the average time to detect the presence / absence of the primary, α is the FAR (False alarm Rate) constraint and $x^+ = \max(x,0)$. Thus we seek a scheme which minimizes the average detection under a FAR constraint. This is an important requirement for cognitive radio.

In the distributed setting there is no known optimal solution of (1) (see [3], [23] and [25] for a state-of-the-art survey). However the algorithm in [20] uses many desirable features to provide a performance better than any algorithm known to us so far.

III. COOPERATIVE SENSING ALGORITHMS

We present DualCUSUM which was developed in [1]. Then we will generalize it.

In DualCUSUM, CUSUM algorithm is run at the local (secondary) nodes. If it crosses a threshold γ then it transmits a message to the fusion node (it just sends a '1' with amplitude b). There is physical layer fusion at the fusion node of all the transmissions from different secondaries. The fusion node also runs CUSUM based on its input and finally declares a change if its CUSUM process exceeds a threshold β. The algorithm is given below.

A. DualCUSUM Algorithm

1) Each of the secondary users l runs Parametric CUSUM algorithm ([14]).

   $$W_{k,l} = \max(0, W_{k-1,l} + \xi_{k,l}),\ W_{0,l} = 0$$
   $$where,\ \xi_{k,l} = \log[f_{1,l}(X_{k,l}) / f_0(X_{k,l})], \qquad (2)$$

   $f_{1,l}$ is the density of $X_{k,l}$ under H_1 and f_0 is the density of $X_{k,l}$ under H_0.

2) Secondary user l transmits at time k, only if $W_{k,l} > \gamma$: $Y_{k,l} = b1_{\{W_{k,l} > \gamma\}}$. The parameters b and γ are chosen appropriately. This censoring allows saving energy, and causing less interference to others.

3) At the fusion center we assume physical layer fusion: $Y_k = \sum_l Y_{k,l} + Z_k$

   where Z_k is i.i.d. noise at the fusion node.

4) Change detection at the fusion center via CUSUM: $F_k = \max\{0, F_{k-1} + \log\frac{g_I(Y_k)}{g_0(Y_k)}\}$

   where g_0 is the density of Z_k and g_I is the density of $Z_k + bI$, I being a design parameter.

5) The Fusion Center declares a change at time $\tau(\beta,\gamma,b,I)$ when F_k crosses a threshold β: $\tau(\beta,\gamma,b,I) = \inf\{k : F_k > \beta\}$.

Although DualCUSUM is not provably optimal, it has some desirable features: (i) it uses past observations at the local nodes as well at the fusion nodes; (ii) local nodes employ censoring before transmitting (this reduces interference to the primary and saves energy) (iii) physical layer fusion is exploited in transmitting the data to the fusion node (this saves transmission time in transmitting data from L cognitive radios). Consequently it has been shown to outperform other known algorithms in literature (see [1], [20]).

In the above algorithm we have assumed that the channel from the secondary users to the fusion center has no fading although that can also be taken care of if the channel gains h_l' are known. Also the same DualCUSUM algorithm works if we want to detect the time when the primary stops the transmission (possibly with different parameters).

If the distribution of T is known, then for a single node, shirayev algorithm is optimal ([11], [23]). One could possibly use that also in our setup at the secondary or fusion nodes. However, especially in cooperative setup, its performance analysis may become intractable.

B. GLR-CUSUM Algorithm

DualCUSUM assumes that both $f_{1,l}$ and f_0 are available. In Cognitive Radio the difficulty is in obtaining perfect knowledge of P_l, the primary's power and the noise power σ_l^2. In this section we modify the DualCUSUM algorithm to obtain GLR-CUSUM algorithm to take care of the uncertainty in P_l.

We replace the CUSUM algorithm used at the secondary nodes by the GLR algorithm ([11]) which also has certain optimality properties. Let the density of $X_{k,l}$ be f_0 before change and f_θ after change, where θ is a parameter that characterizes density after change. Then the CUSUM algorithm at node l declares change at time

$$\tau_{\gamma,l} = \inf\{k : \max_{1\leq s\leq k}(\sum_{i=s}^{k} \log\frac{f_\theta(X_{i,l})}{f_0(X_{i,l})}) > \gamma\}. \qquad (3)$$

When θ is not known exactly but that $\theta \in \Theta \subseteq \Re$ (where $\Re$ denotes real line), then in GLR we declare change at time

$$\tau_{\gamma,l} = \inf\{k : \max_{1\leq s\leq k}(\sup_{\theta\in\Theta} \sum_{i=s}^{k} \log\frac{f_\theta(X_{i,l})}{f_0(X_{i,l})}) > \gamma\}. \qquad (4)$$

It is assumed that the distribution of fusion receiver noise Z_k is $\sim N(0,1)$. Thus the fusion node can still run CUSUM. Typically the channel gain and the receiver noise within the secondary network would be known to the fusion node ([17]). However if it is also not known, then the fusion node can also use GLR.

For the case of variance change, i.e., where pre-change distribution is $N(0,1)$ and the post change distribution is $N(0,\theta^2)$ (note here that σ_l^2 is taken as 1 without loss of generality and $\theta^2 = 1 + P_l$) the $\underset{\theta}{Sup}(.)$ in (4) is explicitly computed and *max*(.) reduces to

$$L_{k,s,l} = (\sum_{i=s}^{k} X_{i,l}^2/2) - (k-s+1)/2$$
$$- ((k-s+1)/2)\log(\sum_{i=s}^{k} X_{i,l}^2/(k-s+1))) \quad \textbf{(5)}$$
$$W_{k,l} = \max_{1\le s\le k}\{L_{k,s,l}\}.$$

If one specifically looks for an increase in variance (which is the valid scenario in cognitive radio as $P_l > 0$, i.e., $\theta^2 > 1$), then (5) is replaced as

$$\theta_{k,s,l}^2 = \max(1, \sum_{i=s}^{k} X_{i,l}^2/(k-s+1))$$
$$L_{k,s,l} = (0.5(k-s+1)(\theta_{k,s,l}^2 - 1) - 0.5(k-s+1)\log(\theta_{k,s,l}^2)) \quad \textbf{(6)}$$
$$W_{k,l} = \max_{1\le s\le k}\{L_{k,s,l}\}.$$

If there is minimum primary power $P_{\min}$, then $\theta_{k,s,l}$ becomes

$$\theta_{k,s,l}^2 = \max(1 + P_{\min}, \sum_{i=s}^{k} X_{i,l}^2/(k-s+1)) \quad \textbf{(7)}$$

In this work we have assumed $P_{\min}$ to be zero as this serves as the limiting case for detecting very low SNR which is of interest in Cognitive Radio.

One limitation of the GLR algorithm as stated above is the requirement of an infinite memory. In ([11]) there are techniques suggested to limit the window length as defined below.

We will need the Average Run Length (ARL) which is defined as the mean time to false alarm under the hypothesis that there is no change. Based on [5], it can be shown that for the decision statistic in (7), the ARL is related to the threshold γ by

$$ARL = K\exp(\gamma)/\sqrt{\gamma} \quad \textbf{(8)}$$

where K is a constant that can be numerically evaluated using formulae available in [5]. Then the suggested modification is to restrict the computation to a window length of past $M = a\log(ARL)$ decision statistic, where a is a design parameter and chosen such that $a > 2/(P_{\min} - \log(1+P_{\min}))$. Hence in each step, the secondary nodes calculate

$$W_{k,l} = \max_{k-M\le s\le k, s\ge 1}\{L_{k,s,l}\} \quad \textbf{(9)}$$

The rest of the algorithm at the secondary nodes and at the fusion nodes are same as steps 2-5 of DualCUSUM.

C. *MGLR-CUSUM Algorithm*

In this section we consider the case, when both noise power and transmit power are unknown to the secondary nodes. Now we assume that the noise power σ_l^2 has a distribution which is not known exactly but is assumed to lie in $[\sigma_{ref}^2/\lambda, \lambda\sigma_{ref}^2]$ where $\lambda > 1$ is an uncertainty parameter. Based on [21], we know that if the received power is less than $[(\lambda - 1/\lambda)\sigma_{ref}^2]$ then robust detection is not possible via the usual means and this is the SNR wall.

In this section we modify the GLR-CUSUM algorithm so that it can be made to work under this uncertainty as well, i.e., there is no SNR wall problem in this method. We continue to assume that there is no uncertainty at the fusion node and hence Fusion center can use CUSUM.

In this scenario since both pre and post change parameters are unknown we cannot use DualCUSUM or GLR-CUSUM. However both the pre-change and post-change distributions belong to a single parameter exponential family $f_\theta \sim N(0,\theta^2)$. To detect a change at the local node, we use log likelihood ratio for the i^{th} hypothesis: the change occurs from θ' to θ'' at time i against the null hypothesis of no change with parameter θ:

$$L_{k,s,l} = \underset{\theta',\theta''}{Sup}\{\sum_{i=1}^{s}\log f_{\theta'}(X_{i,l}) + \sum_{i=s+1}^{k}\log f_{\theta''}(X_{i,l})\}$$
$$- \underset{\theta}{Sup}\{\sum_{i=1}^{k}\log f_\theta(X_{i,l})\}. \quad \textbf{(10)}$$

Thus then, at the secondary nodes,

$$\tau_{\gamma,l} = \inf\{k : \max_{1\le s<k} L_{k,s,l} > \gamma\}. \quad \textbf{(11)}$$

We call this algorithm as modified GLR-CUSUM (MGLR-CUSUM). Of course whenever DualCUSUM and GLR-CUSUM can be used those should be preferred because they perform better than MGLR-CUSUM.

The values $\theta', \theta'', \theta$ are chosen to maximize the Likelihood sum. It can be shown that for the change in variance case for a possible change at a point $1 \le s < k$ this reduces to

$$L_{k,s,l} = \{-s\log(\sigma_{1,l}^s) - (k-s)\log(\sigma_{s+1,l}^k) + k\log(\sigma_{1,l}^k)\}$$
$$where\ \sigma_{s,l}^n = \sqrt{\sum_{j=s}^{n} X_{j,l}^2/(j-l+1)}. \quad \textbf{(12)}$$

Additionally it is shown in [11] that one requires a minimum amount of M^* samples before change. The necessity of this is, as one is looking for a change in variance and if the change occurs very early the algorithm will not be able to detect the change. Also one can show that assuming that change occurs at M^*+1, $\underset{k\to\infty}{Lt} E[W_{k,l}] \to M^*(\log(1+P) - (P/(1+P)))$.

Thus for a threshold γ, M^* needs to be much greater than $\gamma/(\log(1+P_{\min}) - (P_{\min}/(1+P_{\min})))$. Further in this algorithm we are either interested in detecting an increase in variance (Primary OFF→ON) or decrease in variance (Primary ON→OFF). Thus the actual implementation in each secondary node is,

$$W_{k,l} = \max_{M^* \le s < k} \sqrt{L_{k,s,l} 1_{\{\sigma_{s+1,l}^{k} > \sigma_{1,l}^{S}\}}} . \quad \textbf{(13)}$$

The indicator condition in (13) needs to be reversed if we are looking for a decrease in variance. Further it is easy to see that this can be modified to a finite window of $M^* + M$ samples, where M is the window size chosen as in GLR-CUSUM, and $M^* > M$ for robust detection. The full algorithm is described next.

MGLR-CUSUM Algorithm:

1) At the start of spectrum sensing the fusion center informs all secondary nodes the current assumption about the primary channel, say H_0, i.e., primary is OFF. From now on, the fusion center is only interested in detecting OFF→ON transition.
2) Then each secondary node computes the Likelihood ratio $W_{k,l}$ using (13), and is detecting increase in variance.
3) Secondary node l transmits b at time k, only if $W_{k,l} \ge \gamma$.
4) At the fusion center physical layer fusion is assumed and the steps are same as in DualCUSUM.
5) Once the fusion node declares a change from OFF→ON, it sends this decision instantaneously to the secondary nodes which we assume is received without error. The secondary nodes reset the likelihood ratios, and start the process again, with the condition now being to detect a decrease in variance.

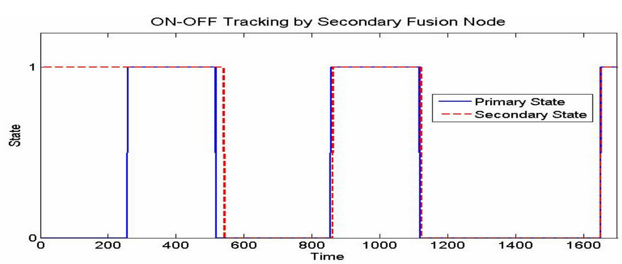

Figure 1: ON-OFF Sequence Detection by MGLR-CUSUM

Figure 1 shows a sample path of MGLR-CUSUM used by 5 secondary nodes, each with SNR of 0 dB, to detect the activity of the primary. In the above sequence initially the primary is OFF, and the fusion center assumed it as ON, and hence the first OFF→ON transition is missed by the secondary nodes, but from then on changes are properly detected. It is noteworthy to add that the threshold γ can be chosen such that, P_{FA} can be different for detecting OFF→ON than for detecting ON→OFF.

D. Performance Comparison

In this section we compare these algorithms with some other known algorithms. We assume that $\sigma_l^2 = 1$ without loss of generality. Primary's power P_l is different in each of the nodes indicating that the channel gains are different for different l.

To illustrate the benefit of sequential change detection techniques, we compare the performance with some simple slot-by-slot detection schemes ([26]). Here each secondary node compares $\log\{f_{1,l}(\hat{\sigma}_{k,l}^2)/f_0(\hat{\sigma}_{k,l}^2)\} > \lambda_l$, where $\hat{\sigma}_{k,l}^2 = \sum_{i=1}^{N} X_{k,l}^2 / N$ and accordingly decides H_1 or H_0 and transmits 1 or 0 to the fusion center (thus exact knowledge of noise power is assumed). We assume that the fusion center receives the same instantaneously without error (although in DualCUSUM/GLR/MGLR-CUSUM we are making the more realistic assumption of noise at the fusion center). Fusion center chooses between H_1 or H_0 according to one of the three fusion rules: **OR**: Change is declared if any secondary decides H_1, **AND**: Change is declared if all secondaries decide H_1 and **MAJORITY**: Change is declared if a majority of the secondaries decide H_1. Also for these algorithms we have compared for $N = 20$ and for an optimum value of N searched via simulations. It shall be noted there exists an optimum value for these algorithms, as increasing N increases probability of detection, but EDD will start suffering beyond a certain value of N.

Parameters used for comparison are as follows. There are 5 nodes and the SNR in dB in these nodes being {-3, -3.5, -4.1, -4.8, -5.2}. The different parameters for our algorithms are chosen appropriately to meet the desired P_{FA}. The change time T is geometrically distributed with $\rho = 1.25e-3$. For fair comparison with the scenario where the noise power is also not known exactly, $(T - M^*)$ is geometric(ρ).

P_{FA}	0.1	0.04	0.01
OR – 20	123.2	241.5	492.7
AND – 20	112.5	175.53	317.8
MAJORITY – 20	72.3	117.26	203.5
OR	88.13	123.77	164.45
AND	89.83	110.87	139.22
MAJORITY	66.81	85.61	103.86
Dual-CUSUM	52.91	70.3	88.91
GLR-CUSUM	55.4	73.6	94.9
MGLR-CUSUM	60.05	79.1	102.4

Table 1: Performance Comparison of Different algorithms

In Table 1 EDD is expressed in units of samples. As can be seen sequential detection algorithms perform better than other algorithms. Although the MAJORITY rule performance is closer to MGLR-CUSUM algorithm, it should be noted that MGLR-CUSUM algorithm does not assume any knowledge of noise and receiver power (thus transmit power and channel gain) and thus is robust. Also in our algorithms we allow for noise at the fusion center. Also we see that optimizing over N in slot-by-slot schemes substantially improves their performance which has not been noticed before.

Next we compare the performance of MGLR algorithm (for one secondary node) against the Rank Statistics based algorithm used in [10]. This is done to illustrate the benefit of MGLR as it utilizes the distribution properties very well. The different parameters for algorithm in [10] are chosen as given in [10]. The

SNR used was 4.77dB. Change time T is fixed at 200. The results are shown in Table 2. As can be seen the performance of MGLR is significantly better.

P_{FA}	0.3	0.2	0.1
Rank Statistics	12.37	20.5	28.2
MGLR	6.57	8.21	10.5

Table 2: MGLR vs. Rank-Statistics

Finally we compare the MGLR-CUSUM algorithm to the algorithm in [15] which is actually a non-parametric cooperative algorithm. There are 5 nodes and the SNR in each node is -3dB. The SNR is kept same at each node to facilitate easier comparison with the algorithm in [15]. The change time T is geometrically distributed with $\rho = 1.25e-3$. The results are shown in Table 3 which shows that MGLR-CUSUM performs significantly better.

P_{FA}	0.1	0.04	0.01
Sahai's Algorithm	72.5	89.95	110.5
MGLR-CUSUM	45.05	55.5	80.01

Table 3: MGLR-CUSUM vs. Sahai's Algorithm

IV. CONCLUSION

We have used the DualCUSUM algorithm presented in [1] for spectrum sensing. DualCUSUM needs the probability densities before and after change. Next we modified it to develop the GLR-CUSUM algorithm to detect change in primary transmission when the received SNR is unknown. The performance of GLR-CUSUM is inferior to DualCUSUM but better than some of the other algorithms. Later on we extend the GLR based algorithm to detect below the SNR wall in a cooperative environment. Comparison via simulations with other algorithms indicates the performance advantage of the sequential detection based algorithms. Future work includes applying these algorithms for other models and optimization for given target constraints.

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