A Review of Cooperative Spectrum Sensing in Cognitive Radios

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Abstract. Dramatically increasing requests for frequency bands in recent years, which has resulted in spectrum scarcity, lead us to examine the feasibility of dynamic spectrum access (DSA) technology. Cognitive radio (CR) has been considered as the key enabler of DSA because of its capability to perform spectrum sensing by using different detection techniques that guarantee acceptable probability of interference to primary users (PU), due to secondary user(s) (SU) access. Furthermore, cooperative spectrum sensing, which combines the observations/decision from a number of CR nodes, in order to determine the presence or absence of a PU signal, can yield better performance than that arrived by a single CR alone. This chapter provides a review of techniques and challenges encountered in cooperative spectrum sensing.

1 Introduction and a Summary of Sensing Methods

Cognitive Radio is built on the software defined radio (SDR) platform with an extra feature, "re-configurability." The idea behind CR is to identify "spectrum holes," performing real-time spectrum allocation and acquisition. This temporarily idle space, which is also known as "white space," is basically the absence of transmission of licensed users. Of course, this space should be vacated in case of re-appearance of primary user(s). For this purpose, following spectrum sensing techniques have been proposed and implemented [1]: matched filter (or pilot) detection (MFD), energy detection (ED), cyclostationary (or characterization) detection (CD), eigenvalue detection (EVD), autocorrelation (or covariance) detection (AD), wavelet detection (WD), and probability-based detection (PD); advantages and disadvantages of these strategies have been reviewed in [2]. Some of these techniques discussed are also presented here. All these techniques are suffering from hidden terminal problem, which could be caused by heavily multipath fading and shadowing effects. The cooperative spectrum sensing has been proposed in order to combat this critical issue [3]; in this work only the hard decision combining, i.e., one bit quantization of CR data has been considered. The soft decision, i.e., multiple bits quantization of CR data was investigated in [4].

S.C. Mukhopadhyay et al. (Eds.): Advancement in Sensing Technology, SSMI 1, pp. 69–80.
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Detection of any phenomenon, based on stochastic data, can lead to errors in decision. When a PU is present, the sensing device could declare that it is not present, leading to a miss, which is the complement of detection. Similarly, when a PU is absent (or spectral hole), the sensing device could declare that a PU is present, leading to a false alarm. If a sensing device is designed to control one type of error, say, the probability of miss P_m, which is One minus the probability of detection ($P_m = 1 - P_d$), below a specified value, the other probability of error, the probability of false alarm P_f, is determined by the quality of the received signal and the noise in the system. From a PU point of view, a larger probability of detection would provide it with better protection, as the chance of a SU transmitting while the PU is present will be less. From a SU point of view a low probability of false alarm is better, as it provides a SU with more access. It is interesting that, depending on the values of these probabilities, one can classify the sensing system in three different categories: *Conservative System* which has an opportunistic spectrum utilization rate less than or equal to 50% and a probability of interference less than 50% that is $P_d > 0.5, P_f \geq 0.5$. *Aggressive System* which expects to achieve more than 50% opportunistic spectrum utilization while maintaining less than 50% probability to interfere with the PU that gives the condition of $P_d > 0.5, P_f < 0.5$. *Hostile System* that targets more than 50% opportunistic spectrum utilization and is likely to cause interference to the PU with a probability greater than or equal to 50% that means $P_d \leq 0.5, P_f < 0.5$ [5].

Furthermore, according to the nature of sensing techniques we can divide the sensing systems into two major groups: Blind sensing that does not rely on any target signal features, like energy detection and autocorrelation detection or signal specific sensing that utilizes specific target signal features, like matched filter detection and cyclostationary detection. On the other hand, IEEE 802.22 standard proposal mentions that no specific spectrum sensing technique is mandatory in the standard and designers will be free to implement whatever spectrum sensing technique they choose as long as it meets the specified sensing requirements [6].

The MFD method provides coherent detection and gives the best performance in terms of signal power to noise power ratio (SNR) as the secondary user receiver assumes the exact knowledge of the signal arriving from the transmission of a primary user. This means necessity of having exact knowledge of the modulation scheme employed by the primary transmitter, time synchronization of arriving symbols, and the channel parameters and if this information is not correct, the MFD performs poorly. In many practical scenarios, such exact knowledge is unavailable and hence it may not be realizable. Of course, the main advantage of MFD is that it needs less time to determine the presence of a PU signal with acceptable probabilities of errors tolerance, when compared to other methods. However, a significant drawback of a matched filter is that a cognitive radio would need a dedicated receiver for every PU class [7].

If a signal exhibits cyclostationary properties, its presence could be detected even in low SNR because CD is capable of differentiating the primary signal from the interference and noise. A signal is cyclostationary, if its autocorrelation is a periodic function. By searching for the peak in the spectral correlation function, the presence of the signal can be identified. It is more robust as noise does not possess any cyclic property whereas different modulated signals have different unique cyclic frequencies. A drawback is that CD is more complex to implement and requires the knowledge of modulation format [1]. We can say CD method, as well as MFD technique, are good to be used in high processing power systems. For more efficient and reliable performance, the enhanced feature detection scheme, combining cyclic spectral analysis with pattern recognition based on neural networks is proposed in [8].

Eigenvalues detection is not computationally complex and primary user waveform information is not required. EVD is based on random matrix theory and auto-correlations are applied on received signal samples thereby estimating the covariance matrix. Then, the maximum eigenvalue of the covariance matrix is compared with predetermined threshold value to determine primary user presence; it has been shown that at lower SNR, EVD has even better results compare to MFD, ED and CD [9].

The Wavelet Detection is based on wavelet transform, which is a multi-resolution method where an input signal is decomposed into different frequency components. By computing the wavelet transform of the power spectral density of received signal, the singularity in spectrum can be located and therefore vacant frequency bands can be found. Again, high sampling rate and computational complexity are the disadvantages. The covariance detection exploits the difference between the autocorrelation of a noise process and that of a signal process in order to sense a PU signal, this technique is suitable for low processing power systems.

The Energy Detection is also termed as a radiometer or a non-coherent detection method. An ED is simply base on Neyman-Pearson approach and computes the energy of a signal present in a certain bandwidth and compares it to certain threshold value to decide whether the desired signal is present or not. The main advantage of ED is that it does not require any knowledge of the signal, such as modulation format or symbol synchronization. When a PU is transmitting, a SU which is located within a reasonable distance from the PU receives the PU signal in noise. The nature of channel between the PU and the SU and hence the power of the received signal in relation to the noise level will impact the performance of the ED. The performance improves with increased signal sensing (observation) time, which, however, results in lapsed opportunity to exploit a significant portion of the duration of PU spectral hole for SU transmission. Moreover, accurate determination of noise level is needed in order to guarantee a certain false alarm probability; error in noise power estimation can result in performance loss. The energy detector shows poor performance in low SNR, because the noise variance is not accurately known at low SNR. Although ED has a simple algorithm when compared to other techniques, at values of SNR below certain threshold, the ED could become useless. Another drawback is the inability of ED to differentiate the interference from other SUs and a PU. There are some other spectrum sensing techniques like multi-tape spectrum estimation (MTSE), which is based on maximal energy concentration of the Fourier transform of Slepian vectors and filter bank spectrum estimation (FBSE), which is a simplified version of MTSE; more details about these methods and a comparison between different sensing techniques could be found in [6]. Also, there is a recently proposed scheme, which is called probability based detection (PD). This method is based on the assumption that the idle duration of the licensed spectrum band is exponentially distributed, so that the probability model regarding the appearance of the primary signal at each sampling point of a CR user frame is established [10].

It is conceivable that the sensing performance of a CR network could be significantly improved, if two or more SUs, who want to opportunistically use the spectrum in a given band, cooperatively sense the presence or absence of a PU in their vicinities. The success of such a cooperative spectrum sensing depends on several factors: first, the SU's ability to cooperate and network among themselves; second, mobile SUs may necessitate dynamically configuring CR networks and third, establishment of a network coordinator or a fusion center, where a final determination based on the sensing data from several SUs could be made. The superiority of cooperative sensing results from the fact that multiple pieces of information from several SUs would be better than one piece of information at a single SU; this is especially true when one of the SU receivers is hidden from a nearby PU transmitter, whereas one or more of other SU receivers in the vicinity of the PU may pick up the transmitted signal. However, there may exists a scenario, where the determination of the presence of a PU by a set of SUs may not be relevant to another SU, simply because the particular PU sensed may really belong only to the "vicinity" of other SUs and not to the one SU under question. This brings up the question of vicinity determination before SUs could cooperatively sense. Hence, one could argue that the determination of a PU is not only with respect to time (present or absent) but also with respect to the location. A detailed discussion of this aspect with ensuing analysis is presented in a recent paper [11]. In this survey, we make the simplified assumption that an appropriate group of cooperative SUs has been determined in order to assess the presence of a PU in their vicinity. Cooperative sensing mechanism draws upon results from distributed detection and its application to wireless sensor networks.

Based upon the distributed detection concept, a cooperative CR system can either use data fusion or decision fusion rules for combining individual observations of CRs. According to the nature of CR networks and their common applications, bandwidth limitation of the reporting (control) channel still remains as a challenge and has been discussed in various literature. In [12], a censoring method for a hard decision scenario is proposed in which every cognitive users obtain an observation independently and determines the reliability of the information and only the users with reliable information were allowed to report their local binary decisions to a common receiver at the fusion center (FC). In that work, the authors studied the performance of spectrum sensing in perfect and imperfect reporting channels and their analytical results show that the average number of sensing bits can be decreased greatly without impacting a great loss of PU detection performance.

2 Cooperative Spectrum Sensing Algorithms and Challenges

Cooperative spectrum sensing, when implemented appropriately, would yield better sensing performance and better throughput in CR networks. Most of the works reviewed here, excluding very recent contributions, have also been included in [13]. In this section, the terms CR and sensor will be used interchangeably.

Different studies have considered different signal models, fusion rules, or performance issues such as, sensing throughput tradeoffs and SNR walls [5, 14-20]. We discuss below some of these results.

In [5], the authors consider energy detection and a large number of samples at the detector so that the ED output can be considered to be Gaussian under both the hypotheses. The mean and variance of the output under the PU present hypothesis are larger than the corresponding values for spectral holes hypothesis. The CRs transmit the ED outputs directly, without any quantization, to a FC over listening channels. After front-end processing at the FC, it is assumed that the received statistic from a CR is a zero-mean Gaussian corrupted version of the transmitted statistic. A LRT at the fusion center will be a linear quadratic statistic and will require computation of multidimensional Gaussian integrals in order to determine the test threshold that meets a specific detection probability at the FC. Because of this computational complexity, a linear combination of received observations was considered. Optimization of weighting vector, for different cases of *Conservative, Aggressive* and *Hostile* systems was considered. For small values of N, the LRT performance was also determined numerically and then compared with that of a linear combiner. The results show usefulness of the linear combiner. In [14], it is shown that the optimization of weights can be done without any approximation and without having to delineate three cases.

In [15], each CR uses identical energy detectors and transmits their binary decisions to the FC over error-free links. The power of the additive noise component in a sensor is assumed to have been estimated by the sensor, with the error in the estimate assumed to be distributed as log-normal with zero mean. Similarly, under the presence of a PU, each CR is assumed to receive a shadowed version of the transmitted PU signal in AWGN noise. For this condition, received power at a CR is modeled as a log-normal distribution with a mean value and a variance that depends on the shadowed-signal variance. Moreover, the signal powers in decibels at two CRs are assumed to have a correlation that decreases exponentially with distance between the receivers. With the assumed knowledge of a minimum value of the mean signal power level at the edge of a PU transmitter range and the goal of keeping the P_m (miss probability, termed as interference probability, the probability of wrongly deciding absence of PU and therefore transmitting SU signal) below a number, a Neyman-Pearson (NP) test was considered. Because of correlated sensor observations, the individual decisions made at the sensors will be dependent. Because of the dependence, a LRT at the FC would require complete joint probability calculations, which would be computationally cumbersome. A suboptimal test based on the sensor decisions, termed linear-quadratic (LQ), was formulated and was shown to provide better performance, i.e., higher probability of spectrum holes detection at a prescribed probability of interference level, than a simple counting rule.

The question of improvement attainable in sending multiple bits (soft decisions) from CRs to the FC, instead of single bits (hard decisions) was examined in [16]. The model assumes the detection of an OFDM signal with cyclic prefix at a CR and assumes a LRT statistic based on the computed autocorrelation coefficient [17]. Assuming the sensor signal observation interval to be very large compared to one OFDM block and that the SNR is small, the distributions of the test statistic under both hypotheses are approximately Gaussian. This becomes a problem of testing two Gaussian distributions with known means and variances. For hard decision combining, the OR, AND, and majority logic (ML), in the class of fusion counting rules were considered. For soft decision combining, the quantizer at a CR was assumed to be a maximum output entropy quantizer and the fusion rule is the comparison of the sum of estimated quantized values against a threshold. The estimated quantized value of a sensor at the FC may differ from the quantized value at the sensor, due to noisiness of the sensor-fusion link. It was assumed the each sensor-fusion is link static and independent of each other, so each exhibits a constant bit error probability (BEP). The theoretical and simulation results show that the ML logic is more robust to bit error probability variations in sensor-fusion (listening channel) link when compared to both OR and AND.

The reference [16] also talks about a BEP wall. The basic idea is that, for the listening channel bit error rate above a certain limit, it is possible that no sensor quality could achieve certain prescribed fusion center performance, specified in terms of both required probabilities, probability of detection (P_{d0}) and probability of false alarm (P_{f0}). Another way to describe this is to calculate the SNR loss in dB defined as the difference between the minimum SNR required at the SUs to meet the constraints on P_{d0}, P_{f0} in the presence of reporting channel errors (P_b) and the minimum SNR required at the SUs in the ideal case of using exact log-likelihood ratio (LLR), an optimal fusion rule and error free reporting channels ($P_b = 0$). A plot of SNR loss against BEP (P_b) was done for soft decision and various hard decision fusion schemes. BEP wall is the point at which the SNR loss increases without bound. BEP wall close to "1" is desirable, since in that case, the cooperative sensing is robust for larger values of BEP. The soft decision combining with two or more bits provide better performance, both in terms of reduced SNR loss and the BEP wall, when compared to hard decision fusion. Among the counting rules examined, ML performs the best. In a related issue, [18] considers the upper bound on P_f (alternatively $1 - P_d$), for a given channel P_b and a specific k-out-of-n fusion rule (counting rule), so that a specified fusion center performance can be met. In other words, if P_f exceeds the bound, the specified fusion center performance cannot be attained. BEP wall basically points out the limitations imposed by the listening channel quality. In [19], the effect of the quality of listening channel on the sensor false alarm and detection probabilities, as seen at the FC, was examined. In that paper, minimum sensor SNR was computed for a prescribed fusion center performance and a given link P_b. Alternatively speaking, since only certain parameters can be controlled by devising a test, under a prevailing condition, certain demands on performance levels may never be met.

In [20], the authors consider a multiband detection procedure for detecting the presence or absence of PUs at the same time. The assumption is that multiple sub-bands within a wideband may be occupied by several PUs and that a simultaneous identification of spectral holes in these sub-bands would allow several SUs to opportunistically transmit their signals. Each sub-band detection is allowed to have different false alarm probability, and hence different sensor detection threshold. By putting a bound on cost function for the interference caused to PUs, and by putting bounds on false alarm and miss probabilities for each sub-band, the authors address the problem of finding optimum sensor thresholds so that the aggregate throughput of all SUs is maximized. The authors show that this optimization problem can be recast into a convex optimization problem so that a computationally feasible solution can be sought. The problem was then extended to the situation of pooled data from all SUs (i.e., cooperative sensing). As in [5], a linear combination of ED sensor outputs was considered. The optimization is now with respect to the weighting vector of the linear combiner and the threshold vector for decisions at the FC (notice that, in this case, no individual decisions are made at a CR). The general optimization problem is not convex; however, by optimizing only the lower bound on the aggregate throughput, and not the exact throughput, the problem can be seen as a convex optimization problem. Simulation results show that cooperative sensing scheme proposed can significantly improve the system performance.

In [21], the authors proposed a cooperative wideband detection scheme with an optimal fusion based on a likelihood ratio test (LRT). In this scheme, which is independent of noise variance estimation, each SU detects the availability of spectrum hole, based on a robust Bayesian estimation algorithm, and then sends their decisions to the fusion center. The authors' simulation results show the effectiveness of the scheme in improving the probability of detection under log-normal shadow fading channel. As mentioned previously, gathering all participating radios data in one place may be very difficult under practical communication constraints [22].

Some distributed cooperative spectrum sensing methods based on consensus algorithms are proposed [23-25]. In [26] consensus schemes for decision fusion-based cooperative spectrum sensing, i.e., OR fusion, AND fusion, and k-out-of-n fusion is investigated. Theoretical analysis shows that by exchanging decision information among adjacent neighboring nodes in a distributed way, these algorithms will converge to the traditional optimal central decision fusion results, assuming that network topology does not change throughout the consensus process.

Another problem addressed is related to finding the optimal number of secondary users. In [27] it was shown that co-operating all secondary users in the network does not achieve the optimum P_d (probability of detection) or P_f (probability of false alarm). The optimum values are usually achieved by exploiting cooperation among a group of users that have higher primary user's signal to noise ratios (SNR). Also, numerical and simulation results provided in [28] show that there exists an optimum number of cooperating users, for a pair of fixed probabilities of detection and false alarm, and cooperating a certain number of users with highest reputation will achieve better sensing performance by accounting for network security.

In [29], the authors consider SNR walls for signal detection. Of specific interest is the spectrum sensing in CR. Given that there will be uncertainty in noise models (noise is never perfectly WGN, noise power measured is uncertain within some non-zero interval), signal models, and transmission channel models (fading parameters can be known only within certain uncertain intervals), dictates of specific false alarm probability and miss probability may not be met, even if the number of independent samples received by a detector become infinitely large. When a radiometer (ED) is used to detect the presence of a weak (very small SNR) unknown signal in AWGN noise, with the noise variance assumed to lie over the uncertainty interval: $[\sigma^2/\rho, \rho\sigma^2] \quad \rho > 1,$ the detector will be unable to meet specified constraints on both $P_f < \alpha < 0.5 \quad P_m < \beta < 0$ if the SNR is below the SNR wall specified by $(\rho^2 - 1)/\rho.$ That is, any amount of sensing time for the radiometer cannot provide the required accuracy. Drawbacks of ED can be clearly seen in this context. If certain information about PU signal, such as the presence of a pilot tone, is known to the radiometer, the SNR wall could be pushed back, but the noise uncertainty still poses a non-zero SNR wall. Thus, if a licensed PU is allowed to transmit any choice signals and at the same time, severe constraint on miss probability for a SU is imposed, the opportunistic spectrum access can yield only a very limited throughput for secondary users. But, if the rules mandate a PU to transmit a pilot at certain power, then SUs can operate more successfully at the cost of potentially lower performance for the PU. This general tradeoff can be seen as capacity-robustness tradeoff [29].

In [30], the authors consider optimizing sensing time in order to maximize secondary user throughput, subject to constraint on interference to PU. Assume a lower bound on the probability of detection (to protect primary user) and an available block of total time out of which a portion of time τ is allocated for sensing and the remaining time for secondary user data transmission, when a SU decides to transmit. Then the problem is to find an optimum τ so that the throughput R of the secondary user is maximized. Notice that R has two components: one when a spectrum hole truly exists, the SU correctly identifies it and the other when a PU is present, but the SU mistakenly considers it to be absent (sneak through case). For radiometer detection it was shown an optimum τ exists and that it can be numerically found. The paper also considers extension to distributed spectrum sensing with multiple SUs. Assuming the knowledge of sensing channels' coefficients, a maximal ratio combiner is considered at the FC. Performance of OR, AND, and ML were also studied.

We discuss now some of the recent contributions to spectrum sensing in CR. In [31] sensing efficiency of the AND, OR, and the *k*-out-of-*n* fusion rules has been discussed, where the authors focus on two important issues of spectrum sensing: the discovered spectrum opportunity and the overall sensing overhead and presented the cooperative spectrum sensing strategies for single and multiple licensed channels. In [32] the authors consider the combining of hard decisions from multiple energy detectors and compare the sensing efficiency for different fusion rules. The optimal decision threshold for the *k*-out-of-*n* rule that can maximize the sensing efficiency was determined and was shown that this rule is optimal in terms of sensing efficiency when compared to tow other rules, for a given false alarm probability. Also, it has been observed that if SU senses the channel over a longer duration, then a lower decision threshold will be required in spectrum sensing, because sensing accuracy will be higher.

In [33] the authors have studied the optimization of cooperative spectrum sensing when the local decisions of the CR users are correlated and a counting rule is employed at the fusion center. Also, the optimal number of users and the local sensing threshold that jointly minimize the probability of sensing error are obtained using the genetic algorithm (GA), when the correlation index is known. Detection performance analysis shows that the cooperative spectrum sensing scheme degrades with an increase in the correlation between CR local decisions for all fusion rules i.e. AND, OR, majority logic and any other counting rule.

In [34] the authors have considered an additional parameter of probability of interference along with the probability of missed detection in order to increase the performance of spectrum hole discovery. Their optimization formulation considers both single and cooperative sensing and the case of one primary user existence. When compared to conventional approaches, their "interference-aware" metric can result in a better utilization of the spectrum by allowing the secondary user to maximize its transmission opportunity, without sacrificing the desired degree of protection for primary users.

Knowing that the reporting channels are not error free in real implementation of CR, in [35] the authors designed a realistic cooperative spectrum sensing network, where the reporting channels from the cognitive radios to the fusion center are affected by AWGN and Rayleigh fading and an optimal minimum mean square error (MMSE) detector is used to improve the detection performance. It is observed that the performance of this detector converges to that of fusion center operating in an ideal (noise free) environment with increasing SNR.

In [36] the authors investigated the performance of cooperative spectrum sensing with cognitive radio users censored on the basis of the quality of Rayleigh-faded reporting channel connecting CR users to a FC. The authors observed that no further improvement in missed detection performance is obtained by increasing the number of CRs beyond a certain limit.

Many analyses presented dealt with cooperative spectrum sensing assuming one primary user. In fact, most of the detection techniques do not require the information about primary users, but in real environment, multiple primary users might exist. In [37] multi-antenna cooperative spectrum sensing in cognitive radio networks, when there may be multiple primary users, is considered. In this approach, sensing performance of a multiple primary users' detector, based on the spherical test (ST) is investigated and also the detection performance is analyzed by deriving closed-form approximations by matching the moments of the test statistics to the Beta distributions, under both hypotheses. Besides, the ST detector estimates whether the covariance matrix differs from a matrix proportional to the identity matrix. According to simulation results, the authors conclude that, in the presence of more than one primary user, some performance gain may be obtained via the spherical test, even without knowing the number of primary users.

3 Conclusion

In this chapter we provided a review of some of the research on cooperative spectrum sensing techniques. The review has not been complete, but an effort was made to present some of the key results. Since the technology for implementation is at an early stage, the topic is of interest to many researchers and we can anticipate more results in the near future.

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