A REVIEW OF SENSING AND DISTRIBUTED DETECTION ALGORITHMS FOR COGNITIVE RADIO SYSTEMS

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Abstract – Optimized spectrum sensing using distributed detection techniques for secondary user spectrum access is becoming important in Cognitive Radio (CR) systems, which have been proposed to utilize the available frequency spectrum more efficiently. For achieving best performance and ensuring minimal acceptable interference to spectrum owners, it is important to accurately sense and detect the presence or absence of primary licensed users. For this purpose, the solutions learned within the framework of distributed detection in wireless sensor networks have been considered. In this paper, we review sensing algorithms and approaches of distributed detection and their relevance to CR systems.

Index Terms: Wireless Sensor Networks, Sensing Techniques, Distributed Detection, Cognitive Radio

I. INTRODUCTION

Increases in the use of wireless enabled devices and the proliferation of mobile phones with demand for voice and data services have necessitated identification of additional frequency spectrum and/or efficient use of existing spectrum. The spectrum available in 900 MHz through 6 GHz region has been licensed to various services in several parts of the world. Also, in existence is the successful operation of wireless devices in the unlicensed Industrial, Scientific and Medical (ISM) radio band. Hence, new services could be provided either through a spectrum underlay mechanism such as Ultra Wide Band (UWB) or a spectrum overlay mechanism [1]. According to a Federal Communications Commission (FCC) report, in a typical period survey, the licensed spectrum usage (e.g. particular police dispatch channel in New York State) ranges from 15% to 85% [2]. Hence, there exist several periods of time intervals when a licensed user is not transmitting signals to its intended recipients. Therefore, periods of no activity, which create spectral holes in the frequency spectrum allocated to the licensed user, could be identified so that other users could utilize the "available" spectrum during those periods. This is the concept behind the opportunistic spectrum access under spectrum overlay mechanism. The term Cognitive Radio (CR) is very relevant to spectrum access [3]. Software Defined Radios (SDR) were developed to give the ability for a wireless transceiver to select, through software and digital signal processing, a particular modulation or demodulation scheme, depending on the channel conditions. Certainly, addition of other cognitive features, such as directional beam forming that avoids interference from other users and the selection of adaptive coding, plus modulation for a specific channel condition, point to the evolution of a software radio as a more sophisticated radio device, a Cognitive Radio [4]. CR is an important component of the IEEE 802.22 standard being developed for Wireless Regional Area Networks (WRAN) for operation in a license-exempt way over the TV broadcast bands. A survey of spectrum sensing in current wireless standards and for the evolving 802.22 standards is discussed in [5]. In the context of opportunistic spectrum access, a licensed user is termed as a Primary User (PU), whereas the other users, who would like to access the spectrum during the absence of primary users, will be called Secondary Users (SU). In a CR network, some secondary users are allowed to use some portions of licensed radio bands opportunistically, provided any interference caused to a primary user is kept below a harmful level. Such an operation of a CR network poses several challenges and opportunities for the development of new devices. Deployment of a CR network involves spectrum sensing, spectrum exploitation, performance evaluation, and optimization at various levels in the network [1, 4]. In this survey paper, we primarily discuss several sensing techniques for CR and survey results from decentralized detection theory that could be applied to cognitive radio networks. First, we discuss various spectrum sensing methods in section II. In section III, we present some key results from distributed detection (also termed decentralized detection) and its applications in wireless sensor networks. Specifically, we discuss data and decision fusion schemes and related configurations. In concluding section, we indicate how results from decentralized detection are applied to cooperative sensing in CR networks. A somewhat detailed survey of detection in cooperative spectrum sensing was given in a conference paper [31].

II. SPECTRUM SENSING TECHNIQUES

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 $(P_d > 0.5, P_f < 0.5)$. *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 $(P_d \leq 0.5, P_f < 0.5)$ [6].

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 [7].

In a CR system, depending on the method employed, spectrum sensing techniques could be implemented using different strategies [9]; Matched Filter (or Pilot) Detection (MFD), Energy Detection (ED), Cyclostationary (or Characterization) Detection (CD), EigenValue Detection (EVD), Autocorrelation (or Covariance) Detection (AD), and Wavelet Detection (WD). 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].

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 primary user class [11].

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 [9]. 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 [12].

An EigenValue Detection is not computationally complex and primary user waveform information is not required. EVD is based on random matrix theory and autocorrelations 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 value of SNR, EVD has even better results compare to MFD, ED and CD [13].

The Wavelet Detection is based on wavelet transform, which is a multiresolution 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 noncoherent 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 [7].

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 exist 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 [8]. 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.

III. DISTRIBUTED DETECTION AND WIRELESS SENSOR NETWORKS

In distributed detection, a set of sensors, possibly geographically dispersed, gathers data regarding the presence (Hypothesis H_1) or absence (Hypothesis H_0) of a target or a phenomenon of interest [14-17]. It is possible that sensors could be deployed to decide on the presence of one of many possible signals (*M*-ary Hypotheses) or to estimate the value of a signal present (estimation problem). While some results developed for the binary case naturally extend to the *M*-ary case (see the above references), many more specific results have been developed for the binary case. In CR context, the phenomenon of interest is the presence or absence of a PU signal and therefore only the binary case is considered in the sequel. Depending on the configuration of processing of signals in general we can say there are two types of distributed (decentralized) decision making rules: Data Fusion and Decision Fusion. Also, there are three major topologies used for distributed detection, which are the results of different approaches and implementations, known as Tree, Parallel and Serial.

1) Sensors can send their observations in a tree structure manner to other nodes; there exist a final root sensor, which is responsible for decision making. Compared to serial and parallel methods given below, tree structured networks need more simultaneous optimizations and are also much more difficult to implement. Figure 1 shows the tree structure topology.

2) Sensors could process its own data only and then send condensed data to a fusion center, where a final determination is made. This approach is called parallel fusion and the topology of this kind of systems is shown in Figure 2.

3) First sensor in a sequence could pass its condensed information to the next sensor in the sequence, which makes its own condensed data based on its own data and the condensed data it had received from the previous sensor, and then passes its condensed data to the next sensor in the chain, and so on, with the last sensor in the configuration making the final decision. According to its nature, this method is known as serial or tandem fusion and is illustrated in Figure 3. An interesting issue in serial fusion is the ordering of non-identical detectors. It might be tempting to put the better detectors toward the end but there exist examples that show that placing the better detectors toward the end need not always be optimal. Ordering depends on many factors such as prior probabilities, costs, etc. and no general result on this issue is available [15].

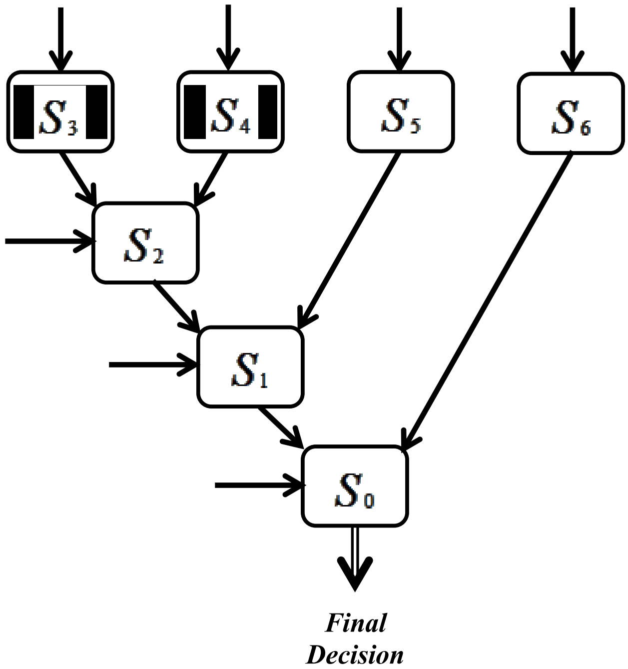

Figure 1. Tree Topology in Distributed Decision

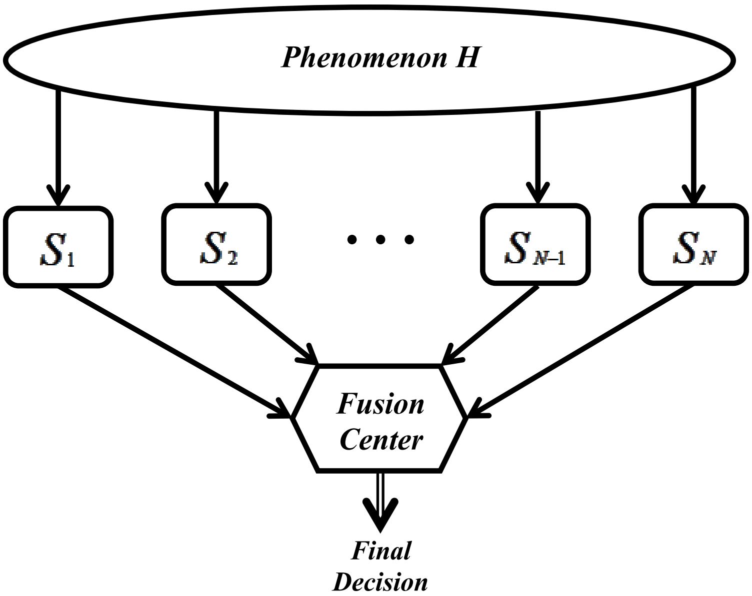

Figure 2. Parallel Topology with Fusion Center

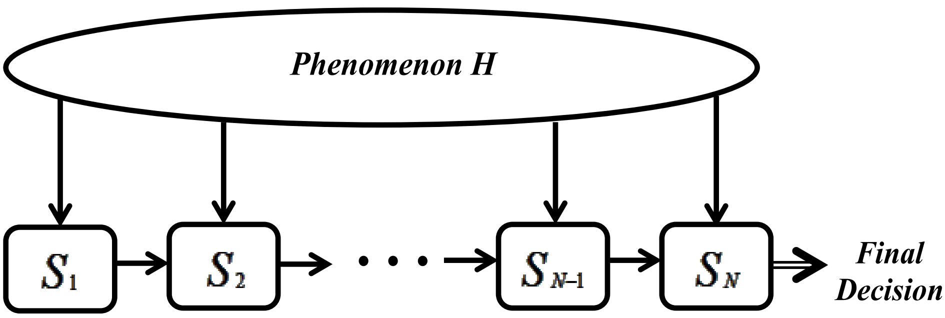

Figure 3. Serial Topology in Distributed Decision

In a Fusion Center (FC) based approaches, assuming that the links between sensors and fusion center, and between the sensors themselves, if configured, are band limited, processing of data at individual sensors is needed so that only a limited or quantized data needs to be sent over these links. In wireless networks, the links are unreliable due to path loss, possible shadowing and fading. Unreliable nature of wireless links implies that a FC may receive possibly a severely corrupted copy of the transmitted condensed data. Hence, in addition to reliability of sensing, reliability of transmission channel plays a determining role in the overall performance of a CR network. The quantized data at a sensor could assume *D* possible values, with *D* equal to two, corresponding to the case that a sensor making the decision on the presence or absence of a PU signals. The binary quantization is the extreme level of quantization or data compression, with the original sensor data representing the other extreme of unquantized data. If sensors send unquantized data to a fusion center over perfectly reliable links, the fusion center could optimally combine the data. Such a fusion scheme is called a Central Fusion scheme, which provides an upper bound on the performance of any scheme based on quantized data and unreliable sensor to FC links.

Consider the case of *D* equal to two; borrowing from classical detection theory, one could determine an optimum test at a sensor, or at the fusion center, based on a well chosen criterion such as, the Bayes criterion or Neyman-Pearson (N-P) criterion. For either criterion, if the sensors observations are conditionally (conditioned on the true hypothesis) independent, it has been shown that the optimum tests at the sensors and at the fusion center are Likelihood Ratio Tests (LRT) based on their own observations. If conditional independence assumption is not satisfied, then the problem becomes N-P Complete [18]. Also, when the sensor observations are conditionally independent and identically distributed (i.i.d), it is asymptotically optimal to have identical likelihood ratio tests at the sensors, as the number of sensors become infinitely large [17]. When tests at the sensors are identical and sensor observations are i.i.d, the likelihood ratio test at the fusion center becomes a counting rule, i.e., the fusion center simply counts, based on the sensor decisions received at the fusion center, how many decisions are in favor of hypothesis H_1 and then declare in favor of this hypothesis if this count exceeds a predetermined threshold, say *k*. If *N* is the total number of sensors, then *k* could be one of $N+$ integer values over the set of 0, 1, 2 … *N*. It can be seen that $k=$ corresponds to the Boolean OR rule, $k=\vee$ corresponds to the AND rule, and $k=\ N+\ )/2$ corresponds the

Majority Logic rule. Depending the requirements of a specific P_f (or a specific P_d), it may be necessary for the fusion center to employ a randomized decision rule, which is randomized between two counting rules with adjacent threshold values. Depending on the underlying distributions of sensor observations under the two hypotheses, it is possible that the probability of miss, at a given probability of false alarm, may not tend towards zero, even when N tends to infinity [19]. Hence, in large networks, extreme counting rules such as, OR and AND have to be used cautiously.

In order to consider the effect of unreliable nature of wireless links on the performance of a wireless sensor networks in detection applications, various methods and performance assessments have been carried out. We consider some of them here [20-24]. Let us assume a parallel configuration of fusion of sensor decisions for detecting a PU. By allowing the number of levels in each sensor (or CR) to be different, say D_i for i^{th} CR, [20] examines the allocation of optimal number of bits in each sensor as:

$$\sum_{i=1}^{N} \log_2(D_i) \leq R$$

Here, the problem is to minimize the probability of error at the fusion center, subject to the above capacity constraint of R bits per unit time carried by a multiple access channel. In the asymptotic case of a large number of sensors, for the problem of detecting deterministic signals in Additive White Gaussian Noise (AWGN), it was shown that having a set of identical binary sensors is optimal. Thus, the benefit of having more sensors, each sending coarse information, exceeds the benefit of getting detailed information from less number of sensors. Similar to this result, analysis of a system under both power and bandwidth constraints shows that it is better to combine many not-so-good local decisions rather than relying on one (or a few) very-good local decisions [21]. In [22], the bandwidth constraint is taken into account by assuming non-orthogonal communication between sensors and the data fusion center via Direct Sequence- Code Division Multiple Access (DS-CDMA) spreading.

When sensors (or CRs) use a binary modulation scheme to transmit their binary decisions to the fusion center, a natural question is whether to combine the demodulator outputs, $Z_i, i = 1,2,\ldots N$ to make a final decision or to make individual decisions V_i, based on each Z_i, and then employ a counting rule for the final decision. If the individual CR error probabilities and the channel state information for each sensor to fusion link are completely known, then a LRT based on Z_i can be implemented. If the sensors do not employ identical tests, then a test based on K_i, termed Chair-Varshney (a LRT based on the individual sensor decisions) can be designed [23]. By observing similarity to diversity combining, one can attempt to combine the demodulator outputs using an Equal Gain Combiner (EGC) or a Maximal Ratio Combiner (MRC). One significance difference between diversity combining and detection in sensor networks is that in the case of former, there is one source and many diversity paths, whereas in the case of latter, not all sensors may decide on the same hypothesis and hence may not be transmitting the same bit. Whereas, in diversity combining, MRC is an optimal, maximal SNR linear combiner, no such optimality exists for MRC in the sensor network context. In fact, in sensor network, MRC performs poorly when compared to EGC and a counting rule in many situations [23, 24]. Interestingly, except for very small SNR, both EGC and the Chair-Varshney rule outperform MRC. Extension of this analysis to a large number of sensors shows that similar comparative performance still holds true [24].

The effect of link quality of the performances of a counting rule and other rules were also addressed in [24]. Each link between a sensor and the fusion center is modeled as an independent and identically distributed slow Rayleigh-Fading binary modulation signal received in AWGN. This study considered the impact of the sensor-fusion center link on the quality of the decision received at the fusion center and the minimum required sensor decision quality, given the availability of a minimum sensor-to-fusion link SNR, in order that the asymptotic (large number of sensors) error in the counting rule classification goes to zero. With a proper choice of threshold for non-coherent On-Off Keying (OOK) detection, it was shown that an asymptotic performance comparable to that of Frequency-Shift Keying (FSK), while achieving some energy saving, is possible.

IV. CONCLUSION

In this review, we have argued that cooperative spectrum sensing, when implemented appropriately, would yield better sensing performance and better throughput in CR networks. We have also indicated the distributed detection algorithms in wireless sensor networks form the basis for cooperative sensing in CR networks. Once we have an appropriate model for observations that sense the presence or absence of a PU in a CR, the results surveyed in this paper are directly applicable to cooperative spectrum sensing. Some of those methods discussed in the literature involve energy detection with log-normal shadowing and sensor correlation accounting for the sensor observation model [25]. Other discussions consider

OFDM type PU signals and employ autocorrelation based spectrum sensing [6, 26-28]. In general, many of those references discuss performance of Boolean rules such as AND, OR, Majority Logic and Likelihood Ratio Tests at the FC. Others discuss different performance issues such as, sensing-throughput trade-offs [30] or alternative ways of performance characterization, such as SNR walls [29]. A detailed study of these methods is beyond the scope of this survey paper.

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