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Spectrum Sensing Algorithms for Cognitive Radio Systems

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ABSTRACT
Future wireless communications systems are expected to be extremely dynamic, smart and capable to interact with the surrounding radio environment. To implement such advanced devices, cognitive radio (CR) is a promising paradigm, focusing on strategies for acquiring information and learning. The first task of cognitive systems is spectrum sensing, that consists the analysis of the radio frequency spectrum. In particular, CR has been mainly studied in the context of opportunistic spectrum access, in which secondary devices are allowed to transmit avoiding harmful interference to higher priority systems, called primary users. Thus cognitive nodes must implement signal detection techniques to identify unused bands for transmission. We focused different spectrum sensing algorithms, focusing on their statistical description and evaluation of the detection performance. We consider the presence of practical impairments, such as parameter uncertainties, and analyze algorithm design. We aim at providing contributions to the main classes of sensing techniques, from basic energy detection, to cooperative eigen value based algorithms, to wideband approaches, touching also simple localization strategies for CR networks. In particular, in the context of energy detection we studied the practical design of the test, considering the case in which the unknown noise power is estimated at the receiver. This analysis allows deepening the phenomenon of the Signal-To-Noise Ratio (SNR) wall, providing the conditions for its existence. This work highlight that the presence of the SNR wall is deter-mined by the accuracy of the noise power estimation process.

Keywords:- Signal to Noise, Spectrum Sensing, Cognitive Radio.

1. INTRODUCTION

A more efficient utilization of the spectrum can be reached through the adoption of flexible devices, able to analyze the surrounding radio environment, discover unused spectrum resources and use them without interfering higher priority users, called primary users (PUs). These actions describe the essential characteristics of the so called opportunistic spectrum access (OSA), where users with a lower priority, named secondary users (SUs), "adopt dynamic spectrum access (DSA) techniques to exploit spectral opportunities". The expression "spectral opportunities" can be generally used to indicate situations in which the SUs have some occasion to transmit. The OSA techniques have been studied in particular in the context of CR. The concept of CR has been defined for the first time by Mitola as a radio system whose behavior is described by the cognitive cycle depicted in Figure-1.

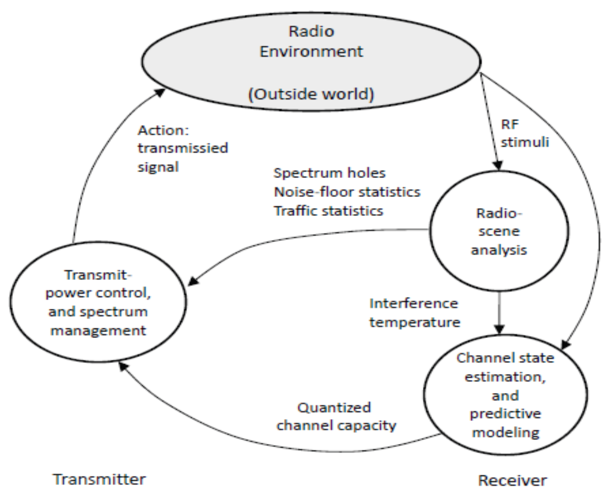

Figure-1: The cognitive cycle.

In order to implement CR devices for OSA the main technological requirements are given by flexible, fast and easily reprogrammable hardware, and proper signal processing algorithms that implement the cognitive functions, such as spectrum sensing and spectrum shaping algorithms, spectrum management strategies, decision and learning techniques, etc.. With regard to the hardware aspects, today we can benefit of so called software defined radios (SDRs) that is a radio equipment designed "trying to push the analog to digital converter (ADC) as close as possible to the antenna", in order to define most of the radio chain components via software. This approach is today possible thanks to modern developments in ADCs and fast electronic circuits. It offers a very high flexibility, allowing most of the parameters to be changed dynamically avoiding excessive time consumption and additional costs. In contrast to traditional radio systems, generally designed to support a particular communication standard, SDRs can potentially allow to change dynamically the standard simply modifying the software that implements its transmit and receive chains.

Spectrum sensing is defined as the capability of the CR to allocate the best available unused or ideal licensed spectrum to the secondary users (SUs) satisfying their Quality of service (QoS) but without causing any interference to the primary or licensed users.

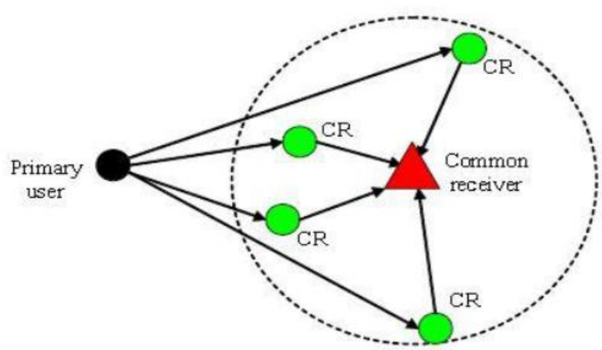

Figure-2: Spectrum sensing structure in a cognitive radio network

II. CLASSIFICATION OF SPECTRUM SENSING ALGORITHMS

In general it is not simple to provide a unique classification of the sensing techniques, especially because there are lots of possible approaches and many algorithms can be included in more than one class. We choose in particular to adopt a classification based on the algorithms practical requirements, defining the following four groups:

(1) Fundamental algorithms: We include in this group the basic algorithms, typically proposed for the observation of a single band, by a single antenna receiver.
(2) Diversity based algorithms: These algorithms require some kind of diversity to be implemented, such as multiple antennas or oversampling.
(3) Wideband algorithms: We include in this group algorithms that are suited for the analysis of multiple bands observations.
(4) Cooperative algorithms: These algorithms are based on the adoption of multiple CR nodes.

2.1 Fundamental algorithms

Since five years ago, many papers dealing with CR introduced the sensing topic asserting that "sensing algorithms can be classified in energy detector, matched filter and cyclostationary detector". Indeed these techniques are the very basic strategies that can be adopted in simple sensing problems, by simple receivers with a single antenna and the observation of a single band.

(i) Energy based detection

The energy detector (ED) is the most simple and popular algorithm for signal detection. Its implementation consists in an estimate of the received power (as sum of the squared received samples) followed by a comparison with a decision threshold. Theoretically the ED is derived as the generalized likelihood ratio test (GLRT) for the detection of a deterministic unknown signal in additive white Gaussian noise (AWGN) or as a sufficient likelihood ratio (LR) statistic when the signal to be detected is described as a zero mean Gaussian process. Its statistic has been widely studied in literature and due to its simplicity of implementation and analysis, currently it is with no doubts the standard sensing algorithm adopted for example in studies on higher level CR functionalities and also by regulatory bodies. Frequency domain EDs have been also proposed. The main impairment of the ED is the fact that its statistic depends on the noise power level, therefore its knowledge is required for setting the decision threshold according to the Neyman-Pearson (NP) approach. In practical applications errors on the noise power level experienced can cause performance losses due to an inaccurate threshold setting and in some cases the rise of the so called SNR wall phenomenon, which is a minimum SNR level under which it is impossible to rich the desired probability of detection (PD) and probability of false alarm (PFA). Recent literature has often emphasized the problem of the SNR wall, giving little attention to the strategies to counteract it, such as how to design noise power estimators that allows avoiding the SNR wall.

(ii) Feature based detection

When some additional knowledge on the signal to be detected is available, we can adopt detectors that exploit this information. In particular, the most common algorithms in this class are:

Autocorrelation based detectors: this algorithm can be adopted when the autocorrelation of the signal to be detected present some peculiar peaks. The most popular autocorrelation based algorithm is the cyclic prefix (CP) based algorithm for the detection of orthogonal frequency division multiplexing (OFDM) signals.

Waveform based detector: If some portion of the primary signal is known, we can build a detector that exploits this knowledge, usually correlating the known feature with the received signal sequence. This can be the case, for example, of signals with known preamble or with some known pilot pattern. The extreme case is the matched filter (MF) detection that requires the knowledge of the complete signal sequence. Even if the MF detector is often cited in SS algorithm surveys, the assumption of perfect knowledge of the PU (and thus the adoption of the MF detector) is unrealistic in practical CR implementations.

Cyclostationarity based detectors: When a signal presents some periodicity in the autocorrelation function, this corresponds to the presence of some correlation in the frequency domain, called cyclostationary feature. As for the autocorrelation features in the time domain, this property can be adopted for detecting PU signals. Many cyclostationary detectors algorithms have been proposed in past literature, usually based on the estimation of the cyclic autocorrelation function or the cyclic spectrum.

2.2 Diversity based detectors

We present some algorithms that can be adopted in presence of some diversity reception mechanism. We refer in particular to multiple antennas system that has been widely studied in current communications literature. The same techniques can be also adopted when we are considering the detection of an oversampled signal. In this situation from the original sample sequence we can extract a number of sub sequences which number correspond to the oversampling factor and use them as they were collected at different antennas. The same algorithms can be also adopted in cooperative sensing system. In all these case studies it is possible to compute the sample covariance matrix (SCM) of the received samples, which is a square matrix with order that equals the degree of diversity of the system. In order to identify the presence of PUs we can adopt threshold based tests which metrics are functions of the SCM. These algorithms are generally called “eigen value based algorithms”. Alternative approaches are based on the information theoretic criteria (ITC).

(i) Eigen value based detectors

The eigen value based algorithms are binary tests in which the decision metrics are functions of the eigen values of the SCM. They have attracted a lot of attention providing good performance results without requiring the knowledge of neither the noise power nor any prior information on the PU signals [65–69]. Considering the most general scenario, with possible multiple PUs, the GLRT is the so called sphericity test, well known in statistics literature and recently re-proposed with the name arithmetic-geometric mean ratio test (AGM). Alternatively, in situations in which we expect to have a single PU, the GLRT is the ratio of maximum eigen value to the trace (MET). Others metrics have been also proposed, such as the Maximum to Minimum Eigen values Ratio (MME). Recently also the case in which multiple antennas are uncalibrated have been considered.

(ii) ITC based detectors

A different approach for the detection of PU signals is to estimate the dimension of the observed sample set. If it contains only the noise the eigen values of the SCM are all equal to the noise power σ^2 otherwise it will contain some eigen value greater than σ^2. This problem can be formulated as a model order selection problem, in which the order of the model is the number of eigen values of the SCM, and it can be solved by means of ITC. If the estimated model order is greater than zero, it means that at least one PU has been detected. Mainly Akaike information criterion (AIC) and minimum description length (MDL) has been adopted. This approach allows implementing detectors that do not need to set a decision threshold.

2.3 Wideband algorithms

Although most of the sensing algorithms have been conceived as single band detectors, wideband SS allows a better knowledge of the surrounding radio environment. Wideband SS consists in a joint observation of multiple frequency bands and joint decision on the occupancy of each sub band. It allows therefore acquiring a more complete observation, avoiding time consuming sequential scan of the spectrum. Its applicability is therefore primarily related to hardware constraints. In CR many approaches have been proposed, starting form “multiband sensing” approaches, that consists simply in dividing the observed band in multiple sub channels. The most common solutions are based on spectral estimation techniques, in addition to some new approaches such as compressive sensing.

(i) Detectors based on spectral estimation

The scope of spectral analysis OS to provide a reliable estimate of the energy distribution in the frequency domain, thus it has a big impact of the environment awareness of the SUs. In CR context non parametric techniques are the more suitable strategies because they do not require any assumptions on the received signal (except the stationary assumption within the observation time) and thus do not require the estimation of any parameters. These approaches in general are constituted by a spectrum estimation stage followed by the adoption of some metric to evaluate the occupancy of each frequency component. The starting point of such techniques is the classical non parametric spectrum estimation theory, based on the periodogram and their derivatives, such as the Welch’s periodogram. The most advanced spectrum estimation approach in this context is the multilayer method. Also advanced filter design strategies can be adopted, such as filter banks approaches. If the SUs know the power spectral density to be detected, the optimum detector in Signal-to-Noise Ratio (SNR) regimes assumes the structure of an estimator correlator.

(ii) Compressive sensing

Compressive sampling is a special signal processing technique that can be applied to signals with a sparse representation. In the context of CR it can be adopted in particular in situations in which the PU signal occupancy is sparse in the frequency domain, exploiting techniques known as compressive sensing. The main advantage of these techniques is that they allow to analyze a large portion of spectrum without the requirement of a high sampling rate.

(iii) Wideband ITC

The wideband sensing problem can be formulated as a model order selection problem, in which the model of the order is the number of frequency bins considered. Then the joint detection of frequency components can be performed using ITC that are commonly adopted for model order selection.

2.4 Cooperative algorithms

A very promising solution for improving the sensing performance of the SU networks is to exploit cooperation among the secondary nodes. In particular cooperative strategies, exploiting the SUs spatial diversity, can be adopted to counteract the channel effects such as multipath and shadowing that cause the hidden node problem. Cooperative SS has reached an increasing attention in the last few years, and many different schemes have been proposed. There are many issues that must be addressed in the design of a cooperative SS strategy. The main requirement is related to the availability of channels for sensing signaling among the SUs that in most of the literature studies is a fixed control channel. In the following we provide a brief classification to highlight their main characteristics. Cooperative algorithms can be classified on the basis of how SUs share their sensing data in the network and in which point of the network the final decision is taken. We have basically two approaches, the centralized and the distributed. Also mixed strategies can be adopted.

(i) Centralized cooperative sensing

In centralized cooperative strategies the sensing information from all the SUs are reported to a central identity, called fusion center that combines them and takes the global decision. Then this information must be sent back to the SUs by means for example of broadcasting.

(ii) Distributed cooperative sensing

Distributed schemes differ from centralized ones for the absence of a specific fusion center. In this case indeed the SUs communicate among themselves and converge to a unified decision. This process can be performed in an iterative way. In this scheme therefore the final decision is taken by each SU on the basis of a common decision policy.

(iii) Mixed strategies

Besides the centralized and distributed approaches, some mixed strategies can be adopted. For example, a relay assisted cooperative scheme can be adopted in cases in which some SUs experience a weak report channel and the remainders can be used for forwarding their sensing results to the fusion center. Another solution is the clustered sensing scheme, in which cluster heads act as second level fusion centers, collecting the sensing results from the SUs within their cluster. Then this data can be shared among other cluster heads or can be forwarded to the fusion center.

With respect to the data that are shared among the SUs, cooperative strategies can be divided in hard fusion and soft fusion schemes:

(i) Hard fusion schemes

When the SUs share their local binary decisions on the presence of PUs, we talk about hard fusion schemes. Locally the SUs can adopt any of the single node sensing techniques described previously. These schemes are convenient for the minimum amount of data that must be exchanged among the secondary nodes. In this case the fusion strategies are typically linear fusion rules such as AND, OR and majority rules. Also Bayesian approaches can be adopted, such as the Chair-Varshney optimal fusion rule.

(ii) Soft fusion schemes

In place to the local binary decisions, the SUs can share richer information, such as their likelihood ratios, in order to improve the sensing result. These schemes require therefore a larger secondary network capacity. Note that the amount of data to be shared depends of the metric chosen and its representation. For example, schemes much closed to hard combining, with only a two bit likelihood ratio representation, has also been proposed. Also in this case linear combining fusion is the most common strategies, such as the Equal Gain Combining (EGC) and Maximal Ratio Combiner (MRC). If the amount of data to be exchanged is not a problem, also algorithms that imply the transmission of all the SUs observations to the fusion center have been proposed. In this case eigen value based algorithms can be adopted also in the cooperative case.

III. MOTIVATION

The cognitive radio offers a very rewarding area of research field. Need of more spectrum due to the under utilization of the available spectrum is the main motivation behind cognitive radio and implementing it leads to lessening of spectrum scarcity and hence the optimal use of spectrum resources. Spectrum sensing which basically checks for the vacant or unused spectrum band forms the main part of the cognitive radio. There are different schemes based on which spectrum sensing is done like energy detector, matched filter detector, Cyclostationary detector, Eigen value based sensing, etc. Energy detector works very well in high SNR environments, matched filter detector needs much more information about the signal which is called priori information and the complexity of other two is high.

IV. EFFECTS OF NOISE POWER ESTIMATION ON ENERGY DETECTION

For single antenna receivers the simplest method to reveal the presence of a signal in AWGN consists in comparing the received energy, measured over a time interval T, with a suitable threshold. This Energy Detector (ED) can be adopted when the signal to be detected is completely unknown and no feature detection is therefore possible. Even when the SU has some knowledge about the signal to be detected, the ED may still be chosen for the simplicity of its implementation. Moreover, for its generality, the ED is commonly used in measurements of the spectral occupation that involve wide frequency bands with different kind of signals. The performance of the ED has been studied in many works including, where a perfect knowledge of the noise power at the receiver was assumed, allowing thus a proper threshold design. In that case, the ED can work with arbitrarily small values of probability of false alarm and arbitrarily high probability of detection even in low SNR regimes, by using a sufficiently long observation interval. However, in real systems the detector does not have a perfect knowledge of the noise power level. Few works deal with the performance analysis of ED when the noise power is not perfectly known.

4.1 Two-step sensing

The simplest way to estimate the noise power is to perform ML estimation on noise-only samples. For impulse radar applications it is quite simple to locate some signal-free samples due to the sporadic occupation of the channel. In CR scenarios instead it is generally much more difficult to guarantee the availability of noise-only samples for environment measurements. We describe the "two-step" sensing schemes, that can be adopted for the implementation of ML noise power estimation. Two-step schemes are motivated by the fact that, while the ED can be used with small sensing periods (even if with limited performance), other more sophisticated sensing methods, with better performance, generally require long observation intervals, with an impact on the efficiency of the SU communications. An effective strategy consists in the combined adoption of sporadic long sensing periods (SPs) for fine sensing (called fine-SPs), and more frequent short SPs (called fast-SPs) in which simpler detectors, such as the ED, can be used shown in Figure-3.

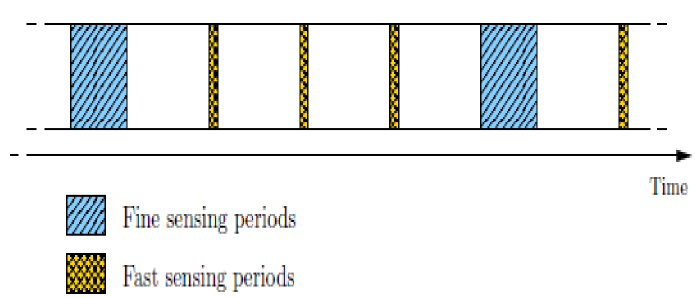

Figure-3: Two step sensing scenario

This two-step sensing scheme is supported by recent CR standards; for example, the IEEE 802.22 draft includes the use of intra-frame periods (5-10 ms) and inter-frame periods (up to 158 ms), while the standard ECMA 392 uses regular SPs, of at least 5 ms, and optional on-demand SPs for further spectral measurements. If, during a fine SP, where a high accuracy detection algorithm is adopted, the decision is for H_0, the samples collected can be considered signal-free; Methods based on multiple antennas can be useful for this task.

4.2 Noise uncertainty

Noise power uncertainty is mainly caused by four factors:

(i) temperature variation;

(ii) change in low noise amplifier gain due to thermal fluctuations;

(iii) initial calibration error;

(iv) presence of interferers.

Noise power estimation with a sufficient rate can be used to overcome the first three factors because thermal changes are very slow phenomena. Indeed the noise power level is stationary typically for a few minutes. The presence of interference caused by other SUs in the CR network instead introduces dynamics in the background RF energy that are too fast to be tackled with periodical estimations. To overcome this problem, the SPs scheduled in the standards IEEE 802.22 and ECMA 392 is synchronized among the SUs to avoid mutual interference. These SPs are called quiet periods. Therefore to avoid the noise uncertainty problem the SU must periodically estimate the noise power during the quite periods.

V. RESULTS AND DISCUSSION

We analyze the performance of the ENP-ED based on the ML noise power estimator, assuming $P_{FA}^{DES} = 1 - P_{FA}^{DES} = 0.1$, as required from the IEEE 802.22 draft standard.

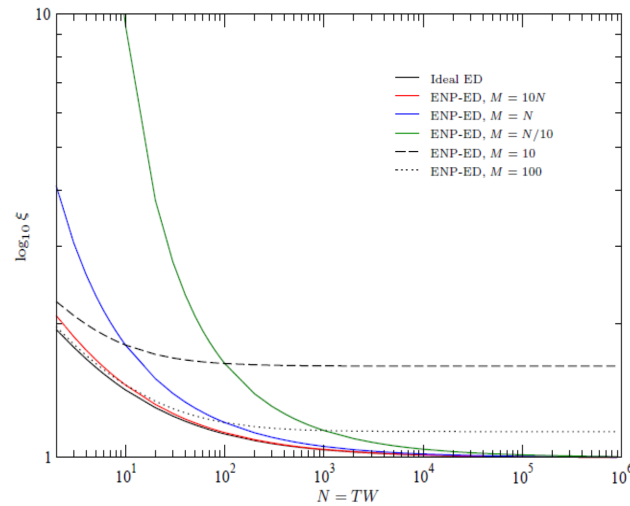

Figure-4: Thresholds as a function of the number of received samples N for $P_{FA}^{DES} = 0.1$.

In Figure-4, we compare the thresholds required for $P_{FA}^{DES} = 0.1$ for the ideal ED and for the ENP-ED.In CR systems, fixing the PD can be more appropriate than fixing the P_{FA}, because of the need of avoid interfering the PUs. We refer to this approach as constant detection rate (CDR) design strategy, where the threshold must be chosen to guarantee PD $\geq P_D^{DES}$ for all SNRs above a given value.

Two-step sensing schemes

In two-step sensing schemes if the SU decides for H_0 in the fine-SP, we propose to use those samples for noise power estimation to set the threshold in the subsequent fast-SP energy detection. We show some numerical performance when the decision is based on a single fast-SP. Note that if the same fine sensing noise level estimate is used for several fast-SPs, the resulting decision variables are correlated due to the same noise level estimate being used.

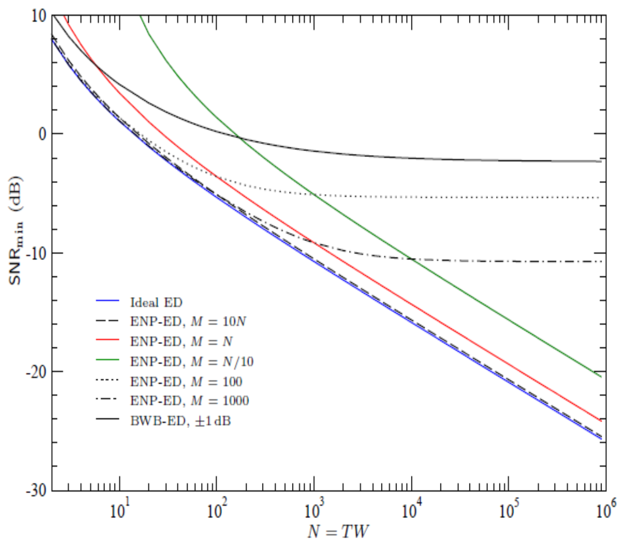

Figure-5: ED and ENP-ED design curves $P_{FA}^{DES} = 1 - P_{D}^{DES} = 0.1$. Noise estimation is performed with M = 10N, N, N/10, 100 and 1000 samples. BWB design curve corresponding to 1 dB noise uncertainty is also shown.

To analyze the ENP-ED with $\hat{\sigma}_{ML}^{2}$ in two-step sensing schemes we report in Figure-5 the curves for M = $\lambda \cdot$ N where λ is thus the ratio between the durations of the fine and fast sensing windows. The difference between the ENP-ED curve and the ideal ED is $10\log_{10}\left(\frac{1+\lambda}{\lambda}\right)$. This is confirmed in the figure, where for M = N and M = N/10 the distance in SNR from the ideal ED curve is about 1.5 dB and 5.2 dB, respectively. The most interesting case for practical situations is when M > N. For instance, if the fine-SP is ten times longer than the fast-SP (M = 10N), the design curve will differ from the ideal one of about 0.2 dB.

VI. CONCLUSION

We focused the problem of Spectrum Sensing in CR wireless networks. We analyzed different sensing techniques, addressing algorithms from the different domains of Spectrum Sensing, from simple energy detection, to cooperative strategies, to wideband sensing. Due to the fact the spectrum holes identification is the primary functionality of Spectrum Sensing, we addressed in particular PU signal detection techniques. We focused on the ED, which is the most popular sensing algorithm due to its simplicity of implementation, and its generality. The ideal ED also provides a good detection performance, that many feature detectors can attain only with a long observation time. The main problem of the ED is that an uncertain knowledge of the noise power level (noise uncertainty) can cause high performance losses, or even the rise of the SNR wall phenomenon, that makes impossible to detect the primary signal with arbitrary probabilities of detection and false alarm. Within the context of cooperative Spectrum Sensing we focused on eigen value based detection techniques, studying the GLRT in the most general case, i.e. making no assumptions on the covariance matrix of the received samples under the signal present hypothesis. When the noise power is the same for all the SUs, the GLRT is the sphericity test. However, in cooperative scenarios the most proper assumption is that every node experiences a different noise power level. The GLRT in this case is the independence test.

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