Chapter 1
Recent Advances on Wideband Spectrum Sensing for Cognitive Radio

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Abstract Spectrum sensing plays a fundamental role in cognitive radio (CR) networks allowing to discover spectrum opportunities and enabling primary user (PU) protection. However, it represents also one of its most challenging aspects due to the requirement of performing radio environment analysis in a short observation time and the fact that its performance can be strongly affected by harsh channel conditions and lack of knowledge about the PU characteristics. In literature, many techniques have been proposed, starting from the most popular algorithms, such as energy detection, to the most advanced, such as, e.g., eigenvalue based detection and cooperative approaches. Most of these techniques have been conceived to assess the occupancy of PUs within a single frequency band. A better knowledge of the surrounding radio environment can be reached exploiting wideband spectrum sensing, that consists in a joint observation of multiple bands and joint detection on the occupancy of each sub-band. Recently, different wideband approaches have been proposed, mainly derived from advanced spectral analysis techniques such as multitaper methods and compressive sensing. In this chapter, we propose a novel methodology for wideband spectrum sensing based on the computation of a frequency domain representation of the received samples and the use of information theoretic criteria (ITC) to identify which frequency components contain PU signals. This technique does not require the setting of a decision threshold, a problem for many spectrum sensing algorithms due to dependence on unknown parameters or difficulties in the statistical description of the decision metrics. We provide a general formulation of the problem, valid for any kind of spectral representation and then focus on the case

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in which discrete Fourier transform (DFT) is used. This choice is motivated by the simplicity of implementation and the fact that DFT blocks are already available in many wireless systems, such as OFDM receivers. This wideband spectrum sensing approach can be adopted by a single CR node in a standalone manner or within a cooperative sensing scheme. Numerical results show that the algorithm derived for DFT can be also applied as an approximated approach when more accurate frequency representations, such as multitaper method (MTM) spectrum estimates, are adopted. Wideband ITC based sensing can be applied in scenarios in which approaches that require a high level of sparsity of the received signal (such as compressive sensing) can not be adopted.

1.1 Introduction

In the last ten years opportunistic spectrum radio assess strategies have gained an increasing interest both in the academia and industries. This fact has been driven by two aspects: the so called *spectrum scarcity* problem and the attempt to reach a more *efficient utilization* of the spectrum resources. Indeed, in spite of the nominal absence of available spectrum, measurements of the radio frequency occupation indicate that large portions of the licensed bands are not used for significant periods of time [1]. Thus, 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 PUs. These actions describe the essential characteristics of the opportunistic spectrum access (OSA), where users with a lower priority, named secondary users (SUs), "adopt dynamic spectrum access (DSA) techniques to exploit spectral opportunities"[1] [3]. The expression "spectral opportunities" can be generally used to indicate situations in which the SUs have some occasion to transmit. In this work, as in most of the CR literature, a spectral opportunity indicates the presence of a portion of spectrum that is temporarily or locally unused. These unoccupied bands are often referred as *spectrum holes* or *white spaces*.[2]

The OSA techniques have been studied in particular in the context of CR. Recently International Telecommunication Union (ITU) defined a CR system as "a radio system employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and its internal state; to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives; and to learn from the results obtained" [5]. Thus we can identify three main key characteristics of CR systems [6]:

[1] The SUs are unlicensed or light-licensed users; in the former case the expression "opportunistic unlicensed access" is often used [2].

[2] The expression "white space" is mainly used with reference to digital television (DTV) bands. It is however accepted as a general term [4].

- capability to obtain knowledge;
- capability to dynamically and autonomously adjust its operational parameters and protocols;
- capability to learn.

Therefore the first step in CR/OSA systems is to implement strategies to acquire information from the radio environment in order to identify ongoing licensed transmissions and preserve them [7]. The main task of this stage consists in identifying which channels are available for opportunistic transmissions, that is equivalent to a PU detection problem. Secondly, it can be useful to acquire some additional information, such as some characteristics of the identified signals, interference measurements, etc.. In literature mainly three solutions have been proposed [2]:

- Geolocation databases;
- Beacon signals;
- Spectrum sensing.

The geolocation database solution is based on the consultation by the SU network of a database that stores the information on the spectral occupancy in the nodes locations and additional information, such as the maximum permitted equivalent isotropic radiated power in each bands. The advantages of this approach are that it is virtually error free and is not affected by radio channel characteristics. However, it is a quite expensive solution. Indeed the secondary nodes require to incorporate some localization technique (e.g. GPS) and Internet connection in order to access the database information. Moreover, additional costs are related to the design, implementation, maintenance and administration of the database, and the costs for gathering the PU occupancy information [8].

The beacon based approach consists in the adoption of a beacon signal that is broadcasted to the secondary nodes providing the PU occupancy information. This solution has a very high infrastructural cost, also requiring some modifications of the current licensed systems. However, some CR networks implementations foresee the adoption of a cognitive pilot channel (CPC) to support cognitive operations such as spectrum allocation [9]. This dedicated channel could be also adopted to convey sensing information towards the SU nodes.

Spectrum sensing (SS) is defined by IEEE as “the act of measuring information indicative of spectrum occupancy” [4]. It consists therefore in the implementation of an autonomous process of the SUs, that on the basis of the received signals analyze the spectrum. It offers the advantage of no infrastructural costs nor modifications in the licensed systems. Moreover, SS makes the SU network completely autonomous and capable of a reactive behaviour. The SU nodes implementation costs depend on the algorithms adopted. The main disadvantages of SS are that its behaviour is generally related to the tradeoff between performance (e.g. detection rate) and observation time and the fact that it can suffer adverse radio channel characteristics, leading to the hidden node phenomenon [7, 10].

The choice of the proper technique to be adopted depends on the particular OSA problem under investigation. In particular, the characteristics of the PUs (such as their temporal dynamics, bandwidth and power) are the most important features to be considered for choosing the proper strategy. Indeed, the adoption of geolocation database fits particularly with highly predictable PUs such as TV signals, that are continuous transmissions broadcasted from known locations. In this case, to evaluate the presence of a TV signal, it could be sufficient, for example, to enquire a database on a daily basis. SS instead is the most promising solution for unpredictable signals that transmit from unknown locations such as programme making and special events (PMSE) signals (like wireless microphones).

The adoption of CR systems is not limited to the licensed spectrum, but they can also operate in unlicensed bands, in which different networks with the same right to access the spectrum are present [11]. Here the main objective is the coexistence of the CR networks that must share the spectrum resources available in an efficient way. In this context SS plays a fundamental role in supporting high level cognitive functionalities such as interference management.

1.1.1 Sensing in the TV White Spaces

In the context the TV white spaces, Federal Communications Commission (FCC) recently decided to remove the requirement that white space devices (WSDs) should implement SS [12]. This decision came after some studies on the minimum sensitivity required at the secondary nodes to ensure DTV and PMSE signal protection in the worst propagation conditions. These analyses showed that common sensing approaches do not guarantee the detection performance required, leaving the implementation of sensing algorithms as an optional feature [12]. However, this decision seems to be moved more by the willing to come up with a regulation on WSDs in a short time, enabling companies to access the white space market, rather than a definitive mistrust in SS strategies. Indeed, the FCC states that [12]:

> Specifically, we are taking the following actions: While we are eliminating the sensing requirement for TV Bands Devices (TVBDs), we are encouraging continued development of this capability because we believe it holds promise to further improvements in spectrum efficiency in the TV spectrum in the future and will be a vital tool for providing opportunistic access to other spectrum bands.

Then, while eliminating SS as a mandatory function, FCC strongly encourages research activities to make possible a sensing based WSDs future generation. In Europe, on the basis of single user sensing algorithms, the European Communications Committee (ECC) came to the same conclusion also suggesting the potential benefit in using a combination of sensing and geolocation database to provide adequate protection to digital TV receivers [13, 14]. It is worthy to note that most advanced sensing techniques have not been considered in the drawing up of these rules. For instance, it is emblematic the case of the ECC report 159 in which, while assessing the benefits of cooperative sensing strategies, the conclusions are drawn considering single node sensing only [14].

In conclusion, in the next few years we expect the born of the first generation of WSDs that probably will be based on geolocation implementation, being the adoption of SS algorithms not mandatory. In spite of this fact, the research community is motivated anyway to continue the investigation in new sensing techniques with the first aim to propose new algorithms with higher detection performances. The most promising approaches consist in advanced techniques based on cooperation among SUs and multiple antennas WSDs, that currently has not been deeply analyzed by regulatory bodies and that deserve more attention in the definition of future rules. More generally, further efforts in SS research must be motivated by the fact that a geolocation database based secondary system can adopt OSA strategies, but cannot be properly considered a cognitive system, due to the lack in autonomy and reactivity to the environment that characterize the original Mitola's proposal, and that only SS can provide. In addition, beyond PU protection, the sensing task has an important role in supporting higher level cognitive functionalities such as resource allocation and spectrum efficiency [15, 16].

1.2 Overview of Spectrum Sensing Algorithms

In this section we present an overview of the main algorithms proposed for SS. 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. Here we choose to adopt a classification based on the detectors' practical requirements, defining the following four groups [17]:

- Fundamental detectors
  We include in this class the basic detectors, typically proposed for the observation of a single band by a single antenna receiver.
- Diversity based sensing
  These detectors require some kind of diversity to be implemented, such as multiple antennas or oversampling. We include in this class the eigenvalue based detection algorithms.
- Cooperative sensing[3]
  These algorithms are based on the adoption of multiple CR nodes.
- Wideband sensing
  We include in this group algorithms that are suited for the analysis of multiple bands observations.

[3] Note that cooperative sensing schemes could be included in the class of the diversity based algorithms, because the adoption of several sensing nodes is essentially a technique for exploiting spatial diversity. However, we separate the class of cooperative algorithms because they have some peculiar characteristics that are not common to other diversity based techniques, such as the selection of the fusion strategy to be adopted, presence of error prone reporting channels, unbalances in the average received power, etc..

In the following we review the main characteristics of the first three classes, while wideband techniques are discussed in the next section.

1.2.1 Fundamental Detectors

Since five years ago, most of the papers on CR introduced sensing asserting that "sensing algorithms can be classified in energy detector, matched filter and cyclostationarity detector". These techniques, indeed, are the very basic strategies that can be adopted in simple sensing problems in presence of single antenna receivers that operate on a single frequency band.

- 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 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 (see e.g. [7, 18, 19]) and due to its simplicity of implementation and analysis, is currently the standard sensing algorithm adopted, for example, in studies on higher level CR functionalities and by regulatory bodies [13, 20]. Frequency domain EDs have also been proposed [21]. The main impairment of the ED is the fact that its statistic depends on the noise power level, which is required for setting the decision threshold according to the Neyman-Pearson (NP) approach [18]. In practice, noise uncertainty can cause performance losses due to an inaccurate threshold setting and in some cases the presence of the so called SNR wall, which is a minimum SNR level under which it is impossible to rich the desired probability of detection (P_D) and probability of false alarm (P_{FA}) [22, 23]. It has been demonstrated that in practical systems proper design of the noise power estimator allows to counteract the noise uncertainty problem [24]. In particular, the conditions for the avoidance of the SNR wall are related to the statistical properties of the noise power estimator [25].

- Feature based detection
  When some additional knowledge on the signal to be detected is available, it can be adopted signal detection. In particular, the most common algorithms in this class are:

  - Autocorrelation based detectors
    These algorithms can be adopted when the autocorrelation of the signal to be detected presents some peculiar peaks. The most popular autocorrelation based algorithms are the cyclic prefix based algorithms for the detection of orthogonal frequency-division multiplexing (OFDM) signals [26–28].

– Waveform based detector
  If some portions 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 preambles or with some known pilot patterns [29]. The extreme case is the matched filter (MF) detector, that requires the knowledge of the complete signal sequence. Even if the MF is often mentioned in SS algorithm surveys, the assumption of perfect knowledge of the PU sample sequence is unrealistic in practical CR implementations [26, 28].
– Cyclostationarity based detection
  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 [30]. As for the autocorrelation features in the time domain, this property can be adopted for detecting PU signals. Many cyclostationary detection algorithms have been proposed in literature, usually based on the estimation of the cyclic autocorrelation function or the cyclic spectrum [30–32].

Feature based algorithms are generally used for detecting the presence of specific PU signals. Being suited for particular communication standards, they are unable to evaluate the presence of different transmissions. The main impairment of these tecniques is the susceptibility to synchronization errors and frequency offsets, that implies the adoption of a synchronization stage [33]. We can consider therefore the feature based detector architecture as a simplified PU signal receiver chain that aims at detecting the presence of the PU transmission, without the need of extracting the information symbols. It is also possible to built general purpose feature detectors, capable, for example, of identifying any possible autocorrelation peak or cyclostationary feature. However these algorithms are very expensive from a computational point of view, time consuming and suffer of synchronization errors [31, 33].

1.2.2 Diversity Based Sensing

In this section we present some algorithms that can be adopted in presence of some diversity reception mechanisms. We refer in particular to multiple antennas systems, that have been widely studied in literature [34]. The same techniques can be also adopted with oversampled signals. In these situations, from the original sample sequence we can extract a set of subsequences which number corresponds to the oversampling factor and use them as they were collected at different antennas [35]. The same algorithms can be also adopted in cooperative sensing systems.[4] In all these cases it is possible to compute the sample covariance matrix (SCM) of the received samples and derive decision tests based on its functions. These algorithms

[4] See footnote 3.

are generally called "eigenvalue based algorithms". Alternative approaches are based on ITC.

- Eigenvalue based detectors
The eigenvalue based algorithms are binary tests in which the decision metric is a functions of the eigenvalues of the SCM. They have attracted a lot of attention providing good performance results without requiring the knowledge of the noise power nor any prior information on the PU signals [36–40]. 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 for SS with the name of arithmetic-geometric mean ratio test (AGM) [36, 40]. Alternatively, in situations in which we expect to have a single PU, the GLRT is the ratio of maximum eigenvalue to the trace (MET) [39]. Others metrics have been also proposed, such as the maximum to minimum eigenvalues ratio (MME) [37], also addressing the case in which multiple antennas are uncalibrated [40, 41].

- ITC based detectors
A different approach for the detection of PU signals is to estimate the dimension of the observed sample set. If we receive only noise, the eigenvalues of the covariance matrix of the observed samples are all equal to the noise power σ^2. Otherwise, if some signals are present, some of them are greater than σ^2. Estimating the number of PU signals is thus a model order selection problem, in which the order of the model is the number of eigenvalues of the covariance matrix, estimated by the SCM. The selection problem can be solved by means of ITC [38, 42]. If the estimated model order is greater than zero, it means that at least one PU has been detected [43]. Mainly Akaike information criterion (AIC) and minimum description length (MDL) have been adopted [43]. This approach allows to implement detectors that do not need to set a decision threshold. Note that this implies that we cannot control the tradeoff between false alarm and detection probabilities.

1.2.3 Cooperative Sensing

A very promising solution for improving the sensing performance of the SU networks is to exploit cooperation among secondary nodes. In particular, exploiting the SUs spatial diversity, cooperative strategies can be adopted to counteract channel effects, such as multipath and shadowing, that cause the hidden node problem [7, 10]. Cooperative SS has reached an increasing attention in the last few years, and many different schemes have been proposed. We refer to [44] and the references therein for an extended overview on cooperative techniques and their principal issues. The main requirement in cooperative sensing is related to the availability of channels for signaling among the SUs, that in most of the literature studies consist in fixed control channels.

Cooperative algorithms can be classified on the basis of how SUs share their sensing data and in which point of the network the final decision is taken. We have mainly two approaches, the centralized and the distributed.[5] Mixed strategies can be also adopted.

- Centralized cooperative sensing
  In centralized cooperative strategies the sensing information from all the SUs is reported to a central identity, called *fusion center*, that takes the global decision. This information is then provided to the cognitive manager of the network that will use it for supporting resource allocation strategies. In some cases the global decision must be sent back to the SUs by means, e.g., of broadcasting [7, 44].
- 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 taken by each SU on the basis of a common policy [44].
- Mixed strategies
  Besides the centralized and distributed approaches, some mixed strategies can be adopted. For example, a relay assisted cooperative scheme can be used in situations in which some SUs experience a weak report channel and the remainders can be used for forwarding their sensing results to the fusion center [44]. 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 a global fusion center. An example of cluster based cooperative sensing can be found in [20].

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

- 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 rule [7].
- Soft fusion schemes
  In place of the local binary decisions, the SUs can share a richer information, such as their likelihood ratios, in order to improve the sensing result. Therefore these schemes generally require a larger amount of data to be shared, mainly depending on the metric chosen and its representation. It has been demonstrated that in many practical situations representing the sensing information with few bits is sufficient for reaching a detection performance equivalent to the unquantized case [45, 46]. If the amount of data to be exchanged is not a problem, algorithms that imply the

[5] Note that in some works the term "distributed" is used as a synonym of cooperative, and expressions such as "non-centralized" are adopted.

transmission of all the SUs' observations to the fusion center have been proposed. In this case eigenvalue based algorithms can be adopted also in the cooperative case [37, 40, 46].

1.3 Wideband Spectrum Sensing: A Review

Most of the SS techniques proposed in literature have been conceived to assess the presence of transmissions within a single frequency band [7]. A better knowledge of the surrounding radio environment can be reached exploiting wideband spectrum sensing, that consists in a joint observation of multiple bands and joint decision on the occupancy of each sub-band. The aim of wideband SS is to distinguish which frequency components contain PU signals from which contain only noise.

Wideband spectrum sensing strategies are generally based on the adoption of some frequency domain representations of the received samples, and thus are related to spectral analysis techniques. The scope of spectral analysis is to provide a reliable estimate of the energy distribution in the frequency domain, and therefore it has a big impact of the environment awareness of the SUs. In CR contexts non parametric techniques are the more suitable strategies because they do not require any assumptions on the received signal.[6] Wideband sensing algorithms are generally constituted by a spectrum estimation stage followed by the adoption of some metric to evaluate the occupancy of each sub-band. The starting point of these techniques is the classical non parametric spectrum estimation theory, based on the periodogram and its derivatives, such as the Welch's method. The most advanced spectrum estimation approach in this context is the multitaper method [47–49]. If the SUs know the power spectral density (PSD) profile of the signal to be detected, the optimum detector in low signal-to-noise ratio (SNR) regimes assumes the structure of an estimator-correlator [50].

The application of wideband SS is primarily related to hardware front-end requirements such as the linearity of analog components and analog-to-digital converters characteristics [51, 52]. To get around such constraints some wideband techniques are based on sequential sensing on multiple bands, frequency sweeping or filter-banks approaches [53–55]. Strategies to reduce hardware complexity have been proposed in the context of compressed sensing, which is a special signal processing technique that can be applied to signals with a sparse representation [56, 57]. 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. The main advantage of this technique is that it allows to analyze a large portion of spectrum without requiring a high sampling rate [57].

Wideband sensing has been also studied in the context of the so called multiband joint detection, that is based on the maximisation of the aggregate opportunistic throughput, a metric that takes into account the trade-off between sensing time and

[6] Generally, the unique assumption is that the received signal samples are taken from a stationary random process.

transmission time in CR systems [58]. In [59, 60] wideband SS has been formalized as a generalized likelihood ratio (GLR) detector, assuming the presence of a given amount of unoccupied spectrum. Alternative wideband approaches are based on ITC, e.g. in [61], where such tools are proposed in a channelized sub-Nyquist scheme. In [62] standard ITC have been adopted to detect the presence of occupied sub-bands using an ED in each sub-band, and a similar approach has been applied to multiband OFDM in [63].

1.4 Wideband Sensing by Model Order Selection

In this section we formulate wideband SS as a model order selection problem solved using ITC. Most of the sensing algorithms proposed in literature are based on the adoption of decision thresholds, which setting is a difficult task in practice due to the dependence on unknown parameters. In particular, considering energy based techniques, including frequency domain analysis, threshold setting depends on the noise power level that must be properly estimated in real implementations [25]. The proposed wideband approach is blind instead, since it does not require the knowledge of the noise power nor any a priori information about the number and the characteristics of the signals present in the observed frequency band.

The proposed wideband sensing technique is based on N observations of a frequency domain vector $\mathbf{x}_i = \left(x_{i,1} \ldots x_{i,q} \ldots x_{i,N_\mathrm{b}}\right)^\mathrm{T}$, where $i = 1, \ldots, N$, and N_b is the number of frequency components considered. We will refer to the elements of $\mathbf{x}_i$ as frequency bins.[7] The problem can be formulated considering a very general approach, in which the vector $\mathbf{x}_i$ can be any kind of frequency domain representation. For instance, it can be a PSD estimate, the output of a filter bank, a compressed sampling reconstruction of the spectrum or, simply, the result of a N_b points DFT.

If PU signals are present in the observed frequency band, we assume that they occupy k^* frequency bins, while the remaining $N_\mathrm{b} - k^*$ contain only noise. Our objective is to identify the occupied k^* bins. In order to accomplish this goal, we formulate wideband SS as a model order selection problem in which k^* is the order of the model [17]. The proposed algorithm estimates k^* and also identifies the occupied bins.

Assuming the radio environment is stationary during the overall sensing period, we collect the N vectors $\mathbf{x}_i$ in the observation matrix

$$\mathbf{Y} = (\mathbf{x}_1 | \ldots | \mathbf{x}_i | \ldots | \mathbf{x}_N) \,. \tag{1.1}$$

Let us sort all vectors $\mathbf{x}_i$ such that the power levels of the frequency bins are now arranged in decreasing order. We denote with $\widetilde{\mathbf{x}}_i$ and $\widetilde{\mathbf{Y}}$ the ordered vectors and the corresponding ordered matrix, respectively. Thanks to ordering, once the model order is estimated, the frequency bins containing PU signals are the first k^* bins of the vectors $\widetilde{\mathbf{x}}_i$. Thus, after recovering the order of the model, we identify the bins that

[7] This is in accordance to the DFT based scenario studied in the following.

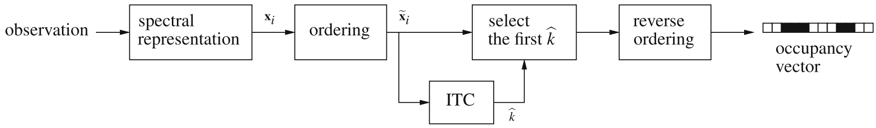

Fig. 1.1 Block diagram of the proposed wideband SS strategy [17]

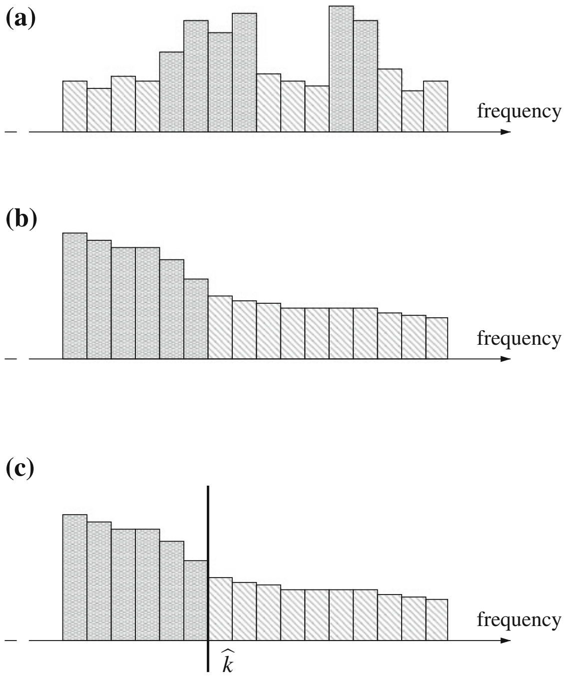

Fig. 1.2 ITC based wideband sensing process [17]. First a frequency representation vector $\mathbf{x}_i$ is collected (**a**) and it is ordered (**b**). Using ITC we obtain $\widehat{k}$ that estimates k^*. Thus the bins that contain signal components are identified as the first $\widehat{k}$ bins of the ordered vector (**c**). **a** Frequency bins vector. **b** Ordering. **c** Selection

contain signal components, and, thanks to a reverse ordering operation, we obtain the occupancy vector, which is a N_b length binary vector in which the q-th element is one if the q-th bin is declared occupied. This wideband sensing process can be represented by the block diagram in Fig. 1.1; the first three steps are depicted in detail in Fig. 1.2. Note that in practical implementations ordering is based on the estimated received power in each frequency bin.

For solving the model order selection problem (i.e. estimating k^*) we adopt ITC, a typical approach used in statistics for choosing the model that better fits data among a family of possible models [64]. In our problem we have N_b possible models, where the k-th corresponds to the case in which we assume that only $k \in \{0, \ldots, N_b - 1\}$ bins are occupied.[8]

To adopt ITC, we start from the analysis of the log-likelihood of the received observation matrix, $\ln f\left(\widetilde{\mathbf{Y}}|\boldsymbol{\Theta}^*\right)$, where $\boldsymbol{\Theta}^*$ is the vector that contains the unknown parameters of the model, which number depends on k^*.[9] According to ITC, the best choice for estimating k^* is given by

$$\widehat{k} = \arg\min_k \left\{-2\ln f\left(\widetilde{\mathbf{Y}}|\widehat{\boldsymbol{\Theta}}^{(k)}\right) + \mathscr{P}(k)\right\} \tag{1.2}$$

where $\widehat{\boldsymbol{\Theta}}^{(k)}$ is the vector of the estimated parameters in the k-th hypothesis and $\mathscr{P}(k)$ is the ITC penalty term.[10] Different choices of the penalty term lead to different criteria, each one characterized by different performance and complexity. In the next section we review the most common and simple techniques, adopted throughout this chapter.

The advantage of using model order selection is that it leads to a blind algorithm which does not require any a priori knowledge of parameters, such as the noise power or PU characteristics. In addition, it does not require the setting of thresholds, avoiding problems such as deriving the exact threshold selection rule. The unique assumption of the proposed strategy is that at least one frequency bin contains only noise. This "minimum sparsity requirement" make this method appealing for scenarios in which wideband algorithms that require a high level of sparsity of the received signal (such as compressive sensing) can not be adopted.

1.4.1 Information Theoretic Criteria

In [65] Akaike first proposed an information theoretic criterion for statistical model identification based on the observation of N independent, identically distributed (i.i.d.) samples of the N_b dimensional random variable (r.v.) $\mathbf{X}$, generated by the "true" distribution $f\left(\mathbf{X}|\boldsymbol{\Theta}^*\right)$. The model selection problem consists in identifying the model that better fits data among a set of possible models

$$\left\{f\left(\mathbf{X}|\boldsymbol{\Theta}^{(k)}\right)\right\}_{k\in\mathscr{K}} \tag{1.3}$$

characterized by the model order k. $\mathscr{K}$ is the set of the possible values assumed by k. Akaike proposed to select the model that minimizes the Kullback-Leibler (K-

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[8] We will refer to the k-th model also as the k-th hypothesis.

[9] Varying the number of occupied frequency bins we have a different set of parameters that describe the model [64].

[10] Using the notation $\mathscr{P}(k)$ we emphasize that the penalty depends on k through the vector $\widehat{\boldsymbol{\Theta}}^{(k)}$. Note that in general $\mathscr{P}(k)$ could also depend on other parameters, e.g. N_b, N and other functions of the observation.

L) distance from $f\left(\mathbf{X}|\boldsymbol{\Theta}^*\right)$, i.e.

$$\widehat{k} = \arg\min_k \mathbb{E}\left\{\ln \frac{f\left(\mathbf{X}|\boldsymbol{\Theta}^{(k)}\right)}{f\left(\mathbf{X}|\boldsymbol{\Theta}^*\right)}\right\}. \tag{1.4}$$

This criterion is equivalent to minimize the cross entropy

$$-\int f\left(\mathbf{X}|\boldsymbol{\Theta}^*\right) \ln f\left(\mathbf{X}|\boldsymbol{\Theta}^{(k)}\right) d\mathbf{X} \tag{1.5}$$

for which a natural estimate, under the k-th hypothesis, is given by the average log likelihood

$$\frac{1}{N}\sum_{i=1}^{N} \ln f\left(\mathbf{x}_i|\widehat{\boldsymbol{\Theta}}^{(k)}\right). \tag{1.6}$$

Akaike noted that the average log likelihood is a biased estimate of the cross entropy, and added a penalty term that asymptotically, for large N, compensates the estimation error. Exploiting the asymptotical chi squared distribution of the log likelihood, Akaike derived the AIC, in which the penalty term is

$$\mathscr{P}_{\text{AIC}}(k) = 2\,\phi(k) \tag{1.7}$$

where $\phi(k)$ is the number of degrees of freedom in the k-th hypothesis. Alternative ITC can be derived adopting the Bayesian approach, which chooses the model that maximizes the posterior probability $\mathbb{P}\left\{\boldsymbol{\Theta}^{(k)}|\mathbf{X}\right\}$ [66]. In this context, the most popular and simple criterion is the Bayesian information criterion (BIC) with penalty term [66]

$$\mathscr{P}_{\text{BIC}}(k) = \phi(k)\ \log N. \tag{1.8}$$

For large enough samples BIC coincides with the MDL criterion, which attempts to construct a model which permits the shortest description of the data [67]. The AIC and BIC approaches are the most popular ITC adopted in many statistical and engineering problems [38, 42, 62, 68]. Although the AIC metric provides an unbiased estimate of the K-L divergence, in many situations it tends to overestimate the true order of the model, even asymptotically [69]. In some cases, consistency can be reached by properly modelling the penalty term [42, 70]. In particular, when the penalty is in the form $\mathscr{P}(k) = \phi(k) \cdot c$, it can be demonstrated that it is required, for N that goes to infinity, that $c/N \to 0$ to avoid underestimation and $c/\log\log N \to +\infty$ to avoid overestimation [71]. Further conditions can be derived in order to solve specific selection problems [72]. Here we consider three consistent criteria, defined by the penalty terms

$$\mathscr{P}_{\mathrm{CAIC1}}(k) = \phi(k)\ (\log N + 1) \tag{1.9}$$

$$\mathscr{P}_{\mathrm{CAIC2}}(k) = 2\,\phi(k)\ \log N \tag{1.10}$$

$$\mathscr{P}_{\mathrm{CAIC3}}(k) = 3\,\phi(k)\ \log N. \tag{1.11}$$

Note that CAIC1 has been proposed by [69] and CAIC2 has been adopted in [68].

An alternative criterion based on the large sample distribution of maximum likelihood (ML) estimators is the consistent AIC with Fisher information (CAICF), which penalty term is [69]

$$\mathscr{P}_{\mathrm{CAICF}}(k) = \phi(k)\ (\log N + 2) + \log \left| \mathbf{J}\left(\widehat{\boldsymbol{\Theta}}^{(k)}\right) \right| \tag{1.12}$$

where $\mathbf{J}\left(\widehat{\boldsymbol{\Theta}}^{(k)}\right)$ is the estimate of the Fisher information matrix (FIM) of the observation and $|\cdot|$ is the determinant operator.

Note that the formulation of the ITC as in (1.2) supports the interpretation of these techniques as extensions of the ML principle in the form of penalized likelihood. The penalty term is introduced as a cost for the increased complexity of the model, related to the presence of unknown parameters that must be estimated [65, 73]. Thus ITC extend the ML approach in the sense that they take into account both the estimation (of the unknown parameters) and the decision (among the possible models) processes. Note that the ML approach performs poorly in model selection problems, always leading to the choice of the maximum number of parameters considered [66].

1.4.2 DFT Based Wideband Algorithms

In this section we apply the ITC based wideband sensing strategy described in Sect. 1.4 to the case in which simple DFT is used as spectral representation of the received signal. We adopt DFT motivated by its simplicity and by the fact that its implementation can be already available in many systems, such as OFDM receivers. In particular, we consider two practical situations with uncorrelated and correlated frequency bins. The first case exploits only the received energy, while the latter jointly exploits the energy level and spectral correlation to discern PU signals from noise.

At the i-th time instant, the output of the DFT can be expressed as

$$\mathbf{x}_i = \mathbf{s}_i + \mathbf{n}_i \tag{1.13}$$

where $\mathbf{n}_i$ represents the AWGN and $\mathbf{s}_i$ is the aggregation of the PUs signals.[11] We assume that the time domain received sample vector is modeled as zero mean complex Gaussian, that is a common assumption in communications literature.[12] Thanks to

[11] Including the channel effects.

[12] This is a proper assumption for many practical problems, such as the case of OFDM signals, that are widely adopted in recent communication systems.

the linearity of the DFT operation, $\mathbf{x}_i$ is a vector of zero mean complex Gaussian r.v.s with covariance matrix $\boldsymbol{\Sigma}_{\mathbf{x}} = \mathbb{E}\left\{\mathbf{x}_i \mathbf{x}_i{}^{\mathrm{H}}\right\}$. After the collection of N DFT outputs we order of the vector $\mathbf{x}_i$ according to the received power in each bin, i.e., according to the vector $\left(\nu_1, \ldots, \nu_q, \ldots, \nu_{N_\mathrm{b}}\right)$, where $\nu_q = (1/N) \sum_{i=1}^{N} \left|x_{i,q}\right|^2$. Thus we obtain a new vector $\widetilde{\mathbf{x}}_i$ with power in each frequency bin in descending order. Note that the vector $\widetilde{\mathbf{x}}_i$ is zero mean with covariance matrix $\boldsymbol{\Sigma}_{\widetilde{\mathbf{x}}} = \mathbb{E}\left\{\widetilde{\mathbf{x}}_i \widetilde{\mathbf{x}}_i^{\mathrm{H}}\right\}$. If the number of frequency bins containing signals is k, $\boldsymbol{\Sigma}_{\widetilde{\mathbf{x}}}$ can be expressed as

$$\boldsymbol{\Sigma}_{\widetilde{\mathbf{x}}} = \boldsymbol{\Sigma}_{(k)} \bigoplus \sigma^2 \mathbf{I}_{N_\mathrm{b}-k} \tag{1.14}$$

where $\boldsymbol{\Sigma}_{(k)}$ is a $k \times k$ submatrix, $\mathbf{I}_p$ is a $p \times p$ identity matrix, σ^2 is the unknown noise power at each frequency bin, and $\bigoplus$ is the direct sum operator [74]. Note in particular that $\boldsymbol{\Sigma}_{(k)} = \mathbb{E}\left\{\widetilde{\mathbf{x}}_{(k)}\, \widetilde{\mathbf{x}}_{(k)}^{\mathrm{H}}\right\}$, with $\widetilde{\mathbf{x}}_i^{\mathrm{T}} = \left[\widetilde{\mathbf{x}}_{(k),i}^{\mathrm{T}}\ \widetilde{\mathbf{n}}_{(k),i}^{\mathrm{T}}\right]$. Then the log-likelihood function of $\widetilde{\mathbf{Y}}$ can be expressed as

$$\begin{aligned} \ln f\left(\widetilde{\mathbf{Y}}|\boldsymbol{\Theta}^{(k)}\right) = &- N_\mathrm{b} N \ln \pi - N \ln |\boldsymbol{\Sigma}_{(k)}| - N\left(N_\mathrm{b} - k\right) \ln \sigma^2 \\ &- N \mathrm{tr}\left\{\boldsymbol{\Sigma}_{(k)}{}^{-1}\, \mathbf{S}_{(k)}\right\} - \frac{N}{\sigma^2} \mathrm{tr}\left\{\mathbf{N}_{(k)}\right\} \end{aligned} \tag{1.15}$$

where $\mathbf{S}_{(k)} = (1/N) \sum_{i=1}^{N} \widetilde{\mathbf{x}}_{(k),i}\, \widetilde{\mathbf{x}}_{(k),i}^{\mathrm{H}}$ and $\mathbf{N}_{(k)} = (1/N) \sum_{i=1}^{N} \widetilde{\mathbf{n}}_{(k),i}\, \widetilde{\mathbf{n}}_{(k),i}^{\mathrm{H}}$.

1.4.2.1 Independent Frequency Bins

In the case in which the frequency bins are independent, $\boldsymbol{\Sigma}_{(k)}$ is diagonal, and the log-likelihood reduces to

$$\begin{aligned} \ln f\left(\widetilde{\mathbf{Y}}|\boldsymbol{\Theta}^{(k)}\right) = &- N_\mathrm{b} N \ln \pi - N \sum_{q=1}^{k} \ln \sigma_q^2 - N\left(N_\mathrm{b} - k\right) \ln \sigma^2 \\ &- N \sum_{q=1}^{k} \frac{\widehat{\sigma}_q^2}{\sigma_q^2} - \frac{N}{\sigma^2} \mathrm{tr}\{\mathbf{N}_{(k)}\} \end{aligned}$$

where $(\sigma_1^2, \ldots, \sigma_k^2) = \mathrm{diag}\{\boldsymbol{\Sigma}_{(k)}\}$ and $(\widehat{\sigma}_1^2, \ldots, \widehat{\sigma}_k^2) = \mathrm{diag}\{\mathbf{S}_{(k)}\}$. In this case the parameter vector is given by $\boldsymbol{\Theta}^{(k)} = \left(\sigma_1^2, \ldots, \sigma_k^2, \sigma^2\right)$, that can be estimated as $\widehat{\boldsymbol{\Theta}}^{(k)} = \left(\widehat{\sigma}_1^2, \ldots, \widehat{\sigma}_k^2, \widehat{\sigma}^2\right)$, where

$$\widehat{\sigma}^2 = \frac{\mathrm{tr}\{\mathbf{N}_{(k)}\}}{(N_\mathrm{b} - k)}. \tag{1.16}$$

Then, removing the terms that do not depend on k, the log-likelihood can be expressed as [17]

$$\ln f\left(\widetilde{\mathbf{Y}}|\widehat{\boldsymbol{\Theta}}^{(k)}\right) = -N \sum_{q=1}^{k} \ln \widehat{\sigma}_q^2 - N\,(N_\mathrm{b} - k) \ln \widehat{\sigma}^2. \tag{1.17}$$

Note that (1.17) corresponds to the result derived in [62]. For the independent frequency components case the number of degrees of freedom corresponds to the length of $\boldsymbol{\Theta}^{(k)}$, i.e. $\phi(k) = k + 1$.

1.4.2.2 Correlated Frequency Bins

In some practical applications, the signals collected present a non negligible spectral correlation (see [75] for some examples). Thus in this section we remove the assumption that the frequency bins are uncorrelated, and we study the most general case, assuming no particular structures for the correlation matrix. In this case the number of degrees of freedom of the model is given by $\phi(k) = k^2 + 1$, that accounts for the $k \times k$ Hermitian matrix $\boldsymbol{\Sigma}_{(k)}$ and the noise power. Adopting the ML estimates $\widehat{\sigma}^2$ and $\widehat{\boldsymbol{\Sigma}}_{(k)} = (1/N)\sum_{i=1}^{N} \widetilde{\mathbf{x}}_{(k),i}\, \widetilde{\mathbf{x}}_{(k),i}^{\mathrm{H}}$, and removing the terms that do not depend on k, from (1.15) we obtain [17, 76]

$$\ln f\left(\widetilde{\mathbf{Y}}|\widehat{\boldsymbol{\Theta}}^{(k)}\right) = -N \sum_{q=1}^{k} \ln \widehat{\alpha}_q - N\,(N_\mathrm{b} - k) \ln \widehat{\sigma}^2 \tag{1.18}$$

where $\widehat{\alpha}_q$ is the q-th eigenvalue of the sample covariance matrix $\mathbf{S}_{(k)}$. In this case the vector of the unknown parameters is given by $\widehat{\boldsymbol{\Theta}}^{(k)} = \left(\widehat{\alpha}_1, \ldots, \widehat{\alpha}_k, \widehat{\sigma}^2\right)$.

1.4.2.3 Performance Metrics

The performance of the wideband approach can be evaluated in terms of probability to correctly detect k^*, $P_\mathrm{k} \triangleq \mathbb{P}\left\{\widehat{k} = k^*\right\}$.[13] The probability of incorrect detection can be evaluated in terms of probability of overestimation, $P_\mathrm{over} \triangleq \mathbb{P}\left\{\widehat{k} > k^*\right\}$, and the probability of underestimation, $P_\mathrm{under} \triangleq \mathbb{P}\left\{\widehat{k} < k^*\right\}$. Note that these performance metrics are very severe metrics; for example, the cases in which $\widehat{k} = k^*+1$ and $\widehat{k} = k^*+10$ are both considered overestimation events, irrespective of the actual distance from k^*.[14]

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[13] Numerical simulations show that the difference between P_k and the probability of correctly identifying the set of occupied frequency bins is very small, which means that when the algorithms correctly estimate k^* they generally correctly estimate also the occupied set. See [17] for some numerical examples.

[14] Note that in some practical applications the adoption of algorithms that tend to overestimate k^* may be used by means of including a protection margin to preserve low SNR PU transmissions.

For some practical cases we will also analyze the probability of detection related to the q-th bin, P_{D}^{q}.

1.5 Cooperative Wideband Spectrum Sensing

The wideband sensing strategy described in the previous section can be also implemented in a cooperative context in which several CR nodes share their occupancy vectors to reach a global decision. We denote as

$$\mathbf{d}^{(j)} = \left(d_1^{(j)}, \ldots, d_q^{(j)}, \ldots, d_{N_\mathrm{b}}^{(j)}\right)^\mathrm{T} \tag{1.19}$$

the occupancy vector of the j-th SU. We assume a centralized approach in which a K out of M rule is applied to assess the presence of PUs in each frequency bin. To focus on the performance evaluation of the proposed sensing strategies, we assume that an error free separate reporting channel is used for sending the local CR decisions to the fusion center (FC). The q-th element of global occupancy vector, $\mathbf{d}^\mathrm{F}$, is given by

$$d_q^\mathrm{F} = \begin{cases} 1, & \sum_{j=1}^{M} d_q^{(j)} \geq K \\ 0, & \sum_{j=1}^{M} d_q^{(j)} < K. \end{cases} \tag{1.20}$$

The choice of the parameter K determines the specific voting rule. Choosing $K = 1$ we implement the OR strategy, which in general allows higher probability of detection. This approach is the most protective toward PUs, but leads to higher false alarm probabilities. The approach that minimize the number of false alarm events is the AND rule, that can be obtained with $K = M$. However, the AND rule allows the secondary network to declare a band occupied only when all the nodes agree upon the presence of PUs, and thus it performs poorly in presence of harsh channel conditions. In order to reach a good trade-off between false alarm and detection probabilities, intermediate values of K can be chosen, such as $K = M/2$ that leads to the so called majority rule, which in some contexts minimize the total error probability [77].

The probability that the q-th each bin is declared occupied is given by

$$P_\mathrm{D}^{q,\mathrm{F}} = \mathbb{P}\left\{\sum_{j=1}^{M} d_q^{(j)} \geq K\right\} = \sum_{h=K}^{M} \mathbb{P}\left\{\sum_{j=1}^{M} d_q^{(j)} = h\right\} \tag{1.21}$$

and can be derived from the single node probabilities of detection P_D^{q}, with $q = 1, \ldots, N_\mathrm{b}$, and the distribution of a Poisson binomial r.v..

1.6 Numerical Results and Discussion

In this section we show some numerical examples to assess the performance of the proposed wideband sensing technique. We compare the ITC algorithms to simple energy based approaches in which the estimated received power of each frequency bin is compared to the decision threshold. We indicate with ED the ideal ED, which assumes that the noise power is known exactly, and with ED_k the estimated noise power (ENP)-ED described in [25] in which the $N_\mathrm{b} - k^*$ bins with lower received power are used for estimating the noise power.[15] The threshold is set according to the Neyman-Pearson criterion considering a probability of false alarm $P_\mathrm{FA} = 0.01$.

1.6.1 Independent Frequency Bins

In this section we consider the case of independent frequency bins, that is the most interesting case in practice due to the fact that most of communication signals are generated by white data sequences, which give spectral uncorrelated transmissions [78].

In Fig. 1.3 we consider the proposed wideband SS strategy using DFT with $N_\mathrm{b} = 128$, in presence of a single white Gaussian signal, that occupy exactly 64 bins, and AWGN. The number of DFT outputs considered is $N = 1000$. We can see that, increasing the SNR, all the consistent ITC present a step wise behaviour, assessing the correct detection probability to a fixed value for high SNR. The AIC instead confirms its non consistent behaviour. The corresponding probabilities of incorrect estimation are shown in Fig. 1.4. We can see that at high SNR P_under goes to zero and an incorrect detection always consists in a false alarm event. Note that this property is very important in CR scenarios, because it implies that ITC never misdetect the presence of PUs if the SNR is sufficiently high. Considering the ED based approaches we can see that they perform quite poorly providing almost 50 % of overestimations for high SNR levels. In Fig. 1.5 we perform the same analysis of Fig. 1.3 in a Rayleigh fading scenario. Here we consider frequency-flat fading on all frequency bins. With respect to the AWGN case we can see that fading has a big impact on the performance of the wideband algorithms, increasing the SNR value at which they reach a target probability of correct detection.

From the previous analysis it emerges that CAICF, $\mathsf{CAIC2}$, and $\mathsf{CAIC3}$ are the ITC algorithms that allows a better sensing performance allowing almost 100 % probabilities of correct detection of the occupied bins set. Compared to simple ED strategies, the proposed wideband ITC algorithms allow a more accurate identification of the occupied bands.

[15] For simplicity, here we do not use the exact distribution of the ordered vector. Thus the ENP-ED approach adopted can be considered as an approximated strategy valid for large samples use cases.

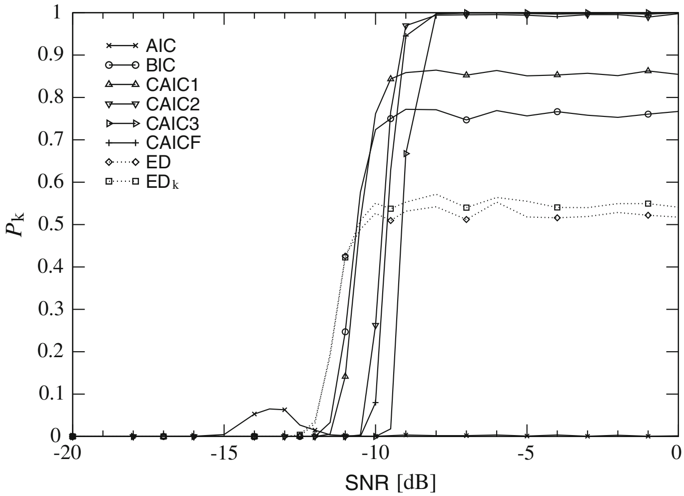

Fig. 1.3 Probability to estimate the correct number of occupied bins as function of the SNR. The number of occupied bins is 64, $N_{\mathrm{b}} = 128$ and $N = 1000$

1.6.2 Correlated Frequency Bins

In presence of frequency correlated observations the wideband ITC approach described in Sect. 1.4.2.2 can be adopted. For simplicity we consider only AIC and BIC, and use the notation $\mathsf{AIC}^{\mathrm{i}}$, $\mathsf{BIC}^{\mathrm{i}}$ to denote the adoption of the independence based algorithm and $\mathsf{AIC}^{\mathrm{c}}$, $\mathsf{BIC}^{\mathrm{c}}$ for the correlated case.

To study the performance of the algorithms we adopt a set of Gaussian samples, generated as an autoregressive sequence, in which consecutive samples have a correlation coefficient ρ. In Fig. 1.6 we show P_{ok} assuming $\rho = 0.8$, $k^* = 64$, $N_{\mathrm{b}} = 128$ and $N = 1000$. Note that in this case the AIC is the algorithm that provides the better performance, reaching $P_{\mathrm{ok}} \approx 1$ at around $\mathsf{SNR} = -3$ dB. Further numerical results assessing the performance of the wideband ITC based technique in the correlated frequency case are provided in [76].

1.6.3 Multiband Sensing

In this section we analyze a multiband scenario in which three OFDM like signals are present in the observed band. The PSD of the spectrum of the three signals is depicted in Fig. 1.7. In the following we indicate with SNR the SNR of the two lower frequency signals. Note that the higher frequency signal has a SNR drop of -3 dB. In Fig. 1.8 we show P_{D}^{q} when the wideband algorithm proposed in Sect. 1.4.2.1 is adopted. It is interesting to note that for very low SNR, such as $\mathsf{SNR} = -20$ dB,

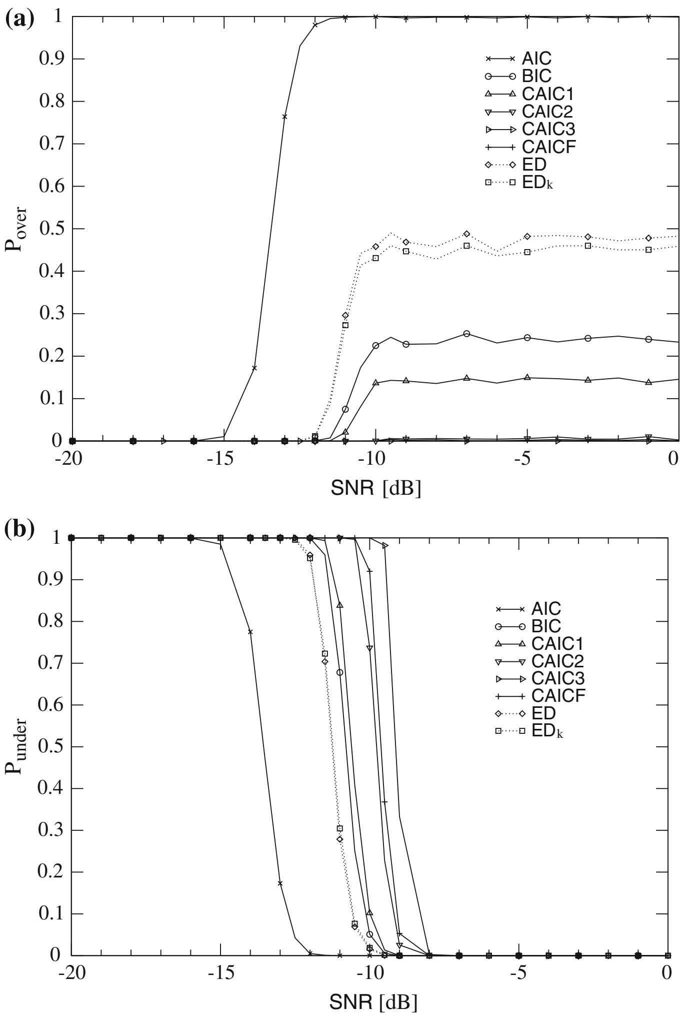

Fig. 1.4 Probabilities to overestimate and underestimate the correct number of occupied bins as function of the SNR. The number of occupied bins is 64, $N_\mathrm{b} = 128$ and $N = 1000$. **a** Probability of overestimation. **b** Probability of underestimation

the algorithm that performs better is the AIC. In Sect. 1.6.1 we noted that generally AIC tends to overestimate the number of bins occupied; this property turns to be an advantage at low SNR levels allowing a better probability to detect the presence of signals. On the other hand AIC always leads to a non negligible number of false alarms in unoccupied bins. From Fig. 1.8b we can see that in this case study all ITC performs well at $\mathsf{SNR} = -10\,\mathrm{dB}$.

ITC are conceived for being statistical approaches that choose the model that best approximates data among a family of models. It is interesting therefore to analyze

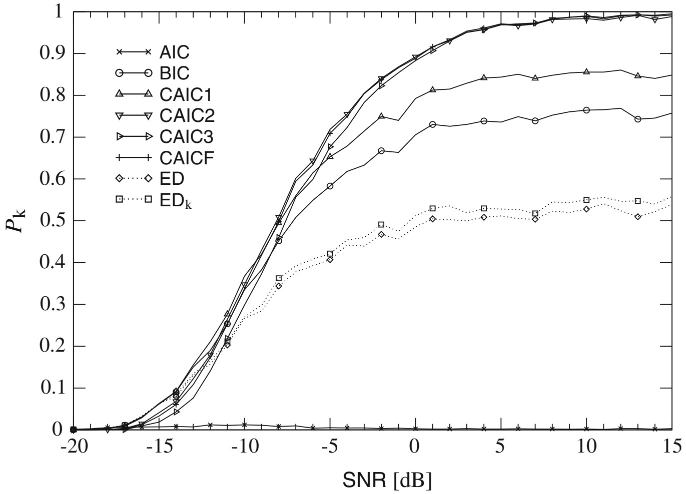

Fig. 1.5 Probability to estimate the correct number of occupied bins as function of the SNR in Rayleigh fading. The number of occupied bins is 64, $N_b = 128$ and $N = 1000$

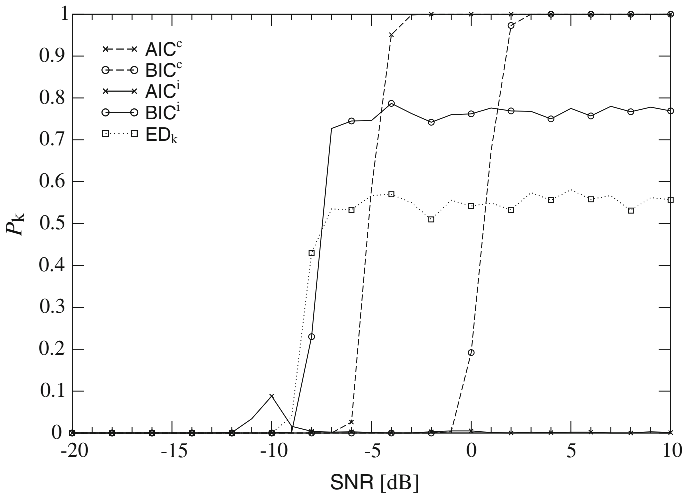

Fig. 1.6 Probability to estimate the correct number of occupied bins as function of the SNR in presence of a frequency correlated signal. The number of occupied bins is 64, $N_b = 128$ and $N = 1000$

if these algorithms provide a good detection performance also when the true model that underlie the generation of the observation is not in the considered model set. This case has also an important impact on practical situations in which the exact statistical description of the collected data is not known or it is too complex to apply ITC in a rigorous way, and thus algorithms derived for simpler models are adopted.

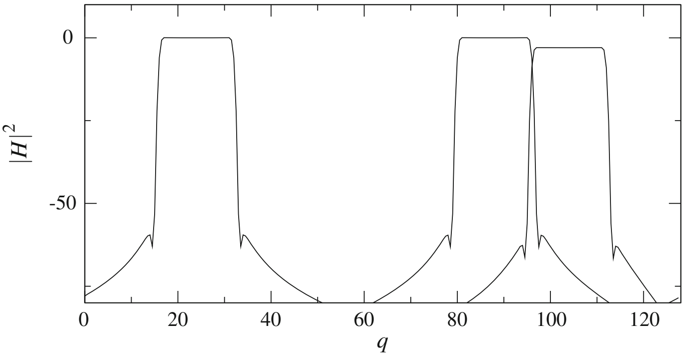

Fig. 1.7 Squared magnitude of the signals adopted in the multiband scenario normalized to 0 dB

Here we consider the case in which the spectral representation used is a spectrum estimate derived using MTM or Welch periodogram, both with N_b points in frequency domain, and we apply the wideband ITC derived for the DFT analysis in Sect. 1.4.2. This can be considered an approximated strategy in which these spectrum estimates, that in general are chi squared distributed, are approximated to Gaussian r.v.s[16] [79]. In Figs. 1.9 and 1.10 we can see that the MTM and Welch strategies provide a very good detection performance that outperforms the DFT based approach for low SNR levels. Then we can benefit from better spectrum estimates (DFT has a non negligible spectral leakage) and apply the wideband approach proposed in Sect. 1.4.2.

1.6.4 Cooperative Wideband Sensing

In Sect. 1.5 we introduced a cooperative sensing strategy that extends single user wideband SS. Here we apply this cooperative approach to the multi band scenario described in the previous section. In Fig. 1.11 we compare the single user P_D^q with the corresponding cooperative performance with different choices of K when AIC is adopted. We consider the presence of $M = 6$ SUs in the AWGN scenario used in Fig. 1.8. When $K = 1$ we implement an OR fusion strategy that provide a very high probability of detection in the occupied bins, but also a very high number false alarms. When $K = M$ we implement the AND rule that allows a very low probability of false alarm, at the expense of a low probability of detection. The performance of the majority rule, with $K = M/2$, is more balanced providing a small number of detection errors in both occupied and unoccupied bins.

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[16] Note that this approximation is valid when the chi squared distribution has a high number of degrees of freedom.

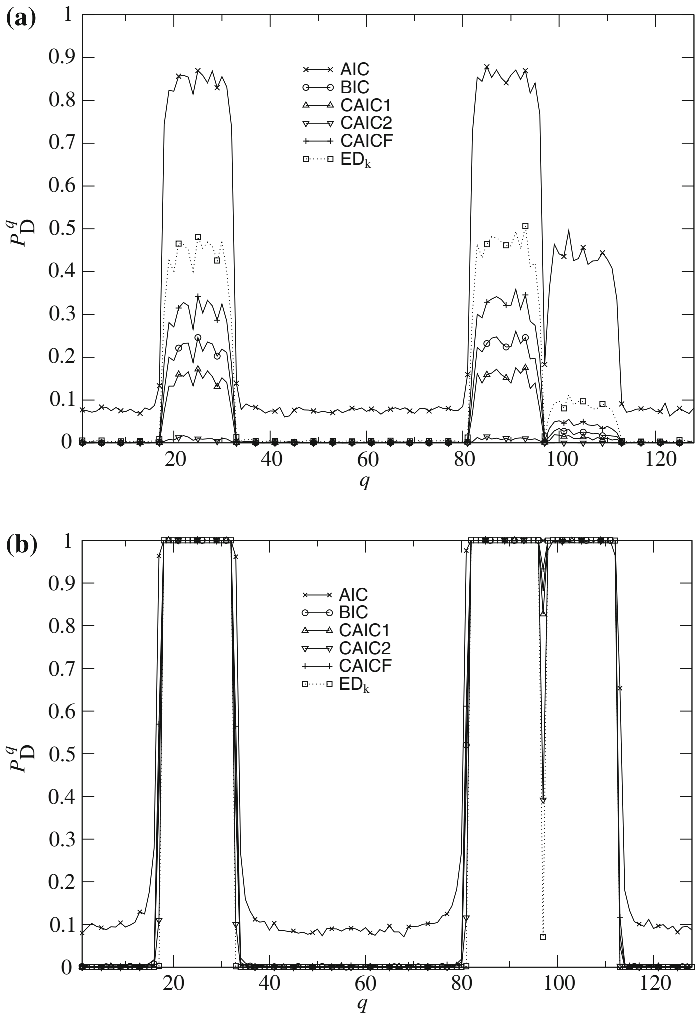

Fig. 1.8 Probability of detection for each frequency bin when the DFT is adopted for the multi band scenario depicted in Fig. 1.7. $N_b = 128$ and $N = 1000$. **a** SNR $= -20$ dB. **b** SNR $= -10$ dB

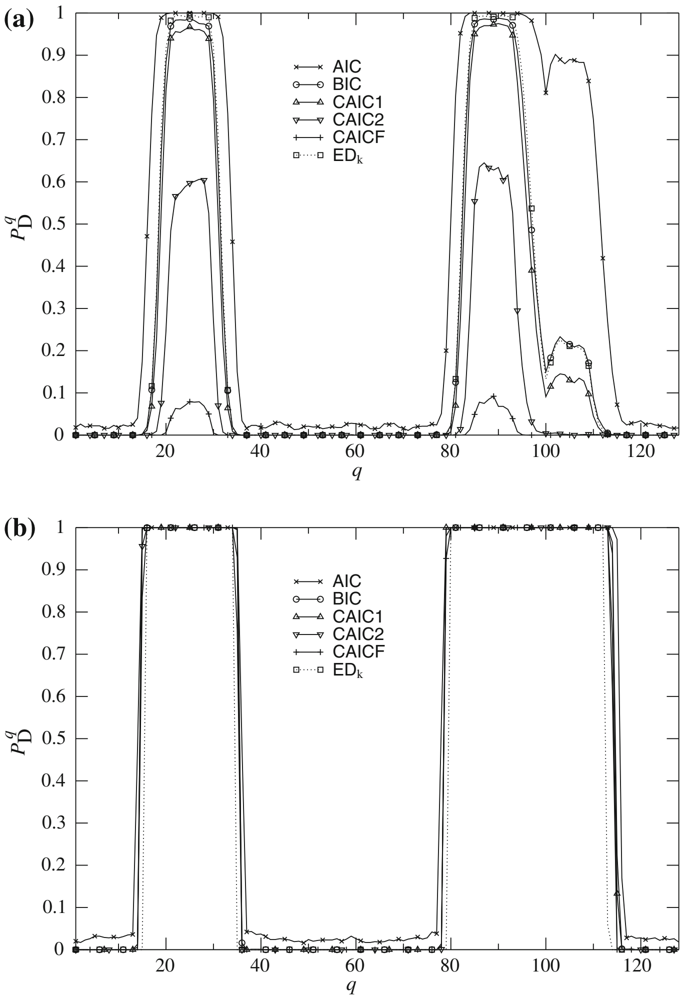

Fig. 1.9 Probability of detection for each frequency bin when a 128 points MTM spectrum estimate is adopted for the multi band scenario depicted in Fig. 1.7. $N = 1000$. **a** $\mathsf{SNR} = -20\,\text{dB}$. **b** $\mathsf{SNR} = -10\,\text{dB}$

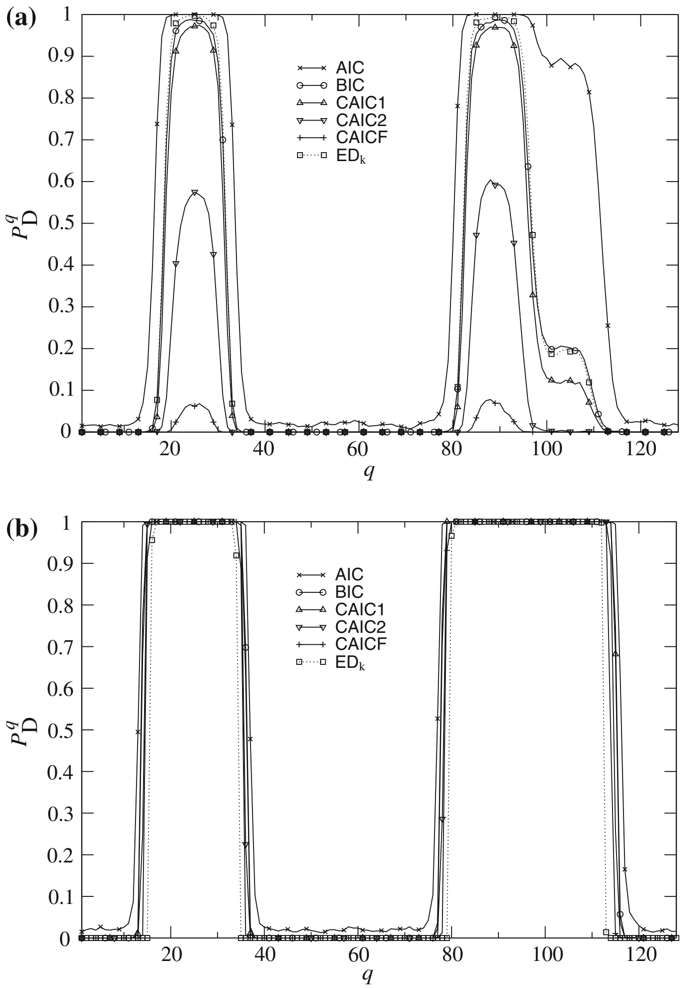

Fig. 1.10 Probability of detection for each frequency bin when a 128 points Welch spectrum estimate is adopted for the multi band scenario depicted in Fig. 1.7. $N = 1000$. **a** $\mathsf{SNR} = -20\,\text{dB}$. **b** $\mathsf{SNR} = -10\,\text{dB}$

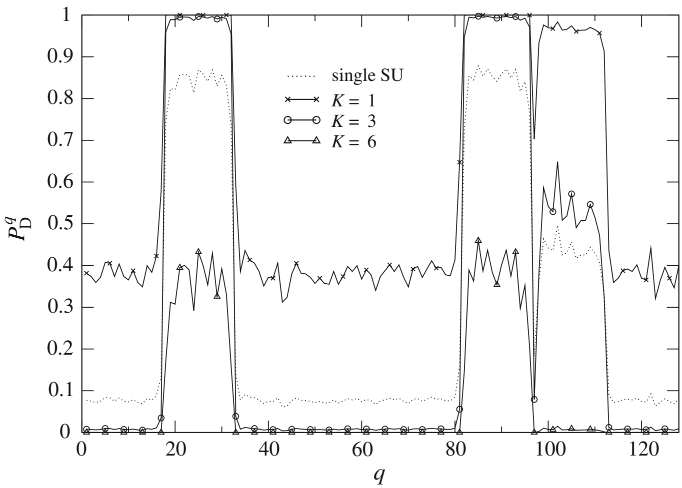

Fig. 1.11 Probability of detection for each frequency bin in a cooperative sensing scheme with six SUs. The fusion rule adopted is the K out of M hard combining. $N_b = 128$ and $N = 1000$

1.7 Conclusions

In this chapter we proposed a wideband spectrum sensing technique based on ITC. We described a general approach that can be applied to any spectral representation and then focused on the simple DFT case. The proposed technique is completely blind since it does not require any knowledge about the noise power and characteristics of the signals present in the observed band. In particular we showed that consistent ITC can reach an almost one probability to correctly identify the number of occupied bins, outperforming simple ED based approaches. Numerical results revealed that this wideband approach can be applied both with independent and correlated frequency components. In particular, the derived DFT based algorithm can be applied as an approximated approach in situations in which the exact distribution of the observation is unknown or too complex, such as when advanced techniques like MTM spectrum estimation are adopted. Wideband ITC based sensing can be applied in scenarios in which approaches that require a high level of sparsity of the received signal (such as compressive sensing) can not be adopted.

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