Measurement Challenges for Spectrum Sensing in Communication Networks

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***Abstract*—We summarize a few key spectrum sensing measurement challenges and recent advances. Laboratory tests of sensing are complicated by their inseparable and often imbedded role in modern hardware. Results are difficult to calibrate because physical parameters are often specified with ad-hoc or unclear definitions. The scope of testing is increased dramatically by sensors that demand more complex signal classification in addition to binary occupancy detection. Tests of spectrum sharing are encumbered even further by a lack of accepted, testable parameters for assessing the contribution of spectrum sensing to spectrum sharing between systems. The measurement needs and approaches we discuss here cross the domains of guided-wave and radiated physical measurements, network measurements, and commercial and government spectrum use.**

I. Introduction

Spectrum sensing is one of the feedback mechanisms used to arbitrate channel access for radio media shared by multiple users or technologies. It is the real-time *in-situ* detection or classification of radiated transmissions from other users, as illustrated in Fig. 1. Transmitting devices, in turn, use this sensing information to make dynamic transmission decisions that support coexistence in the channel.

Sensing may also be used in conjunction with an access database, which authorizes only transmissions in locations, times, or frequencies with low risk of interference to incumbent users. Television transmissions, for example, are protected from transmissions in the whitespace with geographic databasing. While most coexistence in the spectrum commons at 2.4 GHz, 5 GHz, and 6 GHz is based on sensing, as in Fig. 2(a), databases are required by national regulators in some frequencies. The citizens broadband radio service (CBRS), in contrast, depends on centrally coordinated spectrum access to protect incumbent users, which are mostly military naval radars. Transmit grants are awarded to users Fig. 2(b) with a centralized decision and databasing system that is informed by a distributed network of sensors. A more detailed survey of these and other schemes was published recently in [1].

Measurements of spectrum sensors and sensing environments support system-level specification, design, tuning, and final validation. Spectrum sharing feasibility studies require occupancy measurement campaigns [2]. Algorithm design for detection and classification of incumbent transmissions requires signal parameters or training waveforms from real-world radio environments, which are measurable. Network protocols may be co-optimized with sensing capability to maximize the time available for transmission, minimizing unnecessary sensing time. Operators of decentralized networks need field tests to troubleshoot interference. After deployment, stakeholders in shared spectrum allocations need defensible physical measurements to advocate for their coexistence interests to standards bodies and regulators.

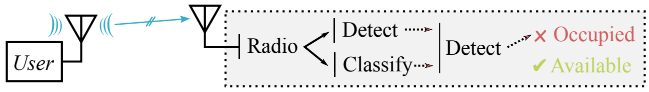
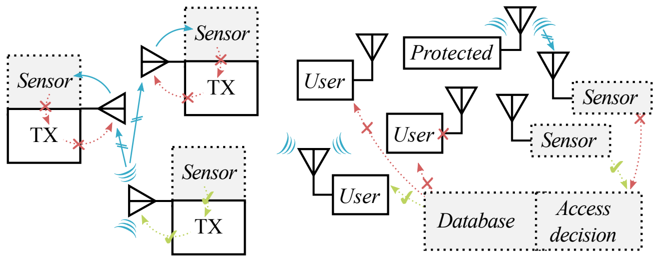


Fig. 1. Spectrum sensing nodes detect channel availability based on the presence (or more detailed classification features) of other users.



(a) Typical unlicensed operation (b) Central coordination in CBRS

Fig. 2. Occupancy status based on incident radio transmissions (solid blue arrows) are detected by sensing nodes. These outputs (dotted lines) serve as feedback for dynamic spectrum access decisions in real-time. In unlicensed spectrum commons (a), each spectrum user is responsible for this sensing before transmission. Centrally-coordinated access in CBRS (b) depends instead on a distributed sensor network to protect incumbents.

We begin our survey by discussing the key measurements and experiments needed to support spectrum sensing, and challenges in making these generally applicable. Then, we consider two application examples: the uncoordinated spectrum commons near 2.4 GHz, 5 GHz, and soon 6 GHz, and the coordinated and tiered CBRS near 3.5 GHz in the United States. These complementary sharing schemes demonstrate test cases for more general test and measurement needs.

II. Metrology for Sensor Performance

The purpose of this field is to connect sensing performance parameters to "ground truth" physical conditions that are traceable to standards in national metrology institutes. First, we summarize some operation and performance parameters for both binary detection and signal classification sensing. Then,

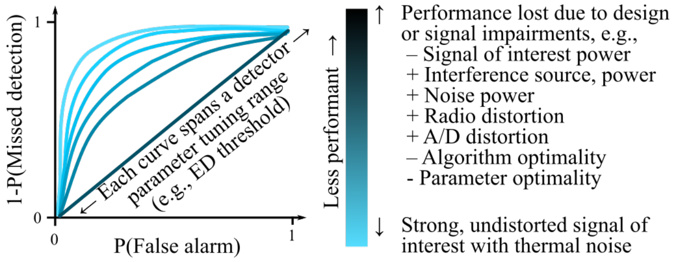


Fig. 3. ROC curves shown for a hypothetical sensor. Each represents the false alarm and missed detection tradeoff for a specific combination of sensing algorithm, hardware impairments, and radio environment.

we consider the physical measurements needed to characterize this performance, and propose a few key research areas that could lead to sensor traceability.

A. Binary Detection Performance

Binary detection deals with an "on/off" status of a signal of interest (SOI) on the channel being sensed. This limits it to relatively simple sharing applications. This approach has been popular for uncoordinated channel access systems such as wireless local area network (WLAN) and LTE-LAA systems, and in cognitive radio applications.

There are many popular methods for binary detection, such as energy detection (ED), entropy detection, covariance matrix-based detection, eigenvalue-based detection, and generalized likelihood ratio tests [3], [4]. Each detector's performance is concerned by two types of errors: missed detection (i.e., false negative) and false alarm (i.e., false positive). Selecting thresholds in these algorithms configures tradeoffs between these errors.

The ED detector, which is the most widely used, indicates the presence of SOIs when averaged waveform energy exceeds a minimum threshold. Detection sensitivity can be improved by increasing the observation window time. But it may experience a limit known as the "SNR wall," which is caused by a bounded noise uncertainty variance [3]. Missed detections occur frequently if SOI power falls below the threshold; false alarms result from other undesired signals.

A popular approach to evaluating binary detection performance is the use of receiver operating characteristic (ROC) curves. The idea is to illustrate tradeoffs between the competing objectives of minimizing both missed detections and false alarms [5], as shown in Fig. 3, swept along a range of tuning parameters. As an example, for ED detectors, it is common that the ED energy threshold is this tuning parameter. Often, as shown here, several curves are compared on the same plot, in order to compare different combinations of algorithms and signal impairments.

The metrology approach to producing trustworthy ROC curves from experimental data requires propagation of measurement uncertainties from physical parameters into the ROC domain. Uncertainties around the curve produce an ROC region, which has been proposed in geo-sensing applications [6]. The area enclosed by the ROC region may in many cases be a small fraction of the total probability space. Yet, the interval may still be significant — particularly in applications with strict incumbent protection requirements, for which the probability of missed detection must be very close to 0.

B. Classification Performance

More complex spectrum sharing applications involve multiple SOIs from users of more than one system and radio access technology (RAT), and mixed across time, frequency, space, and coding. This requires classification of these features in received signals, and details such as the number of carriers, and the modulation scheme, among other properties. The information can then be used to help map the radio environment and to properly schedule network transmission. To achieve this, multiple-signal separation and classification are required. Signal separation can utilize signal processing in spatial and code domains, such as multiple-input multiple-output (MIMO), beamforming, and spreading codes. After signals are separated, feature-based [7], likelihood ratio-based [8], or deep learning based [9] methods can be used to identify the RAT or modulation format of each SOI.

Feature-based classification assigns properties that may lie in time, frequency, space and code domains. For example, spatial feature patterns include antenna array response, MIMO, beamforming, and direction of arrival. Code features include frequency- and time-domain spread codes, and preamble and pilot patterns in orthogonal or non-orthogonal multicarrier multiple access modulation schemes. Cyclostationary signal processing is a common way to extract and identify these signal features.

An ROC curve could be plotted for each of the classifier's SOIs. It is common to summarize this information instead, with a confusion matrix, as in e.g., [10]. Each row and column of this matrix represents one of the N SOIs supported by the classifier, and takes the form

$$\begin{array}{c} \\ SOI_1 \\ SOI_2 \\ \vdots \\ SOI_N \end{array} \begin{array}{c} \begin{array}{cccc} SOI_1 & SOI_2 & \cdots & SOI_N \end{array} \\ \left[\begin{array}{cccc} P_{1,1} & P_{1,2} & \cdots & P_{1,N} \\ P_{2,1} & P_{2,2} & \cdots & P_{2,N} \\ \vdots & \vdots & \ddots & \\ P_{N,1} & P_{N,2} & & P_{N,N} \end{array}\right] \end{array}.$$

Each $P_{k,l}$ represents the probability that a classifier outputs SOI_l given an actual input of SOI_k. Thus, each $1 - P_{k,k}$ is the missed detection probability for SOI_k, while for each $k \neq l$, $P_{k,l}$ is a conditional probability of false alarm. The corresponding (unrealizable) performance ideal for a classifier is therefore described by a confusion matrix equal to the identity matrix I_N.

Each $(k,l)^{\text{th}}$ entry in the confusion matrix can be regarded as an ROC curve that has been simplified to a single point by fixing tuning parameters to constants. The number of measurements must therefore scale up to accommodate the $N \times N$ matrix entries comprising $P_{k,l}$, instead of the 2 required for an ROC curve.

C. Physical Parameters

Laboratory measurements of ROC or sensitivity must sample across a large space of input conditions (such as in Fig. 3), and connect ROC curves and confusion matrices to traceable physical quantities and fundamental SI units. The measurement values can also be provided with estimated uncertainties in order to propagate statistical errors to high-level network parameters like latency and throughput.

1) SI-traceable noise measurement: Basic power quantity measurements of weak signals, interference, and noise can be traced to fundamental physical standards for noise standards through calibration. This process, in turn, can be traced further to the Kelvin, which is one of the seven fundamental units.

Spectrum regulators have assigned many spectrum allocations with bandwidths on the order of only a few percent, so noise calibrations must be performed at fine resolution. Today, however, noise calibrations are limited to a small handful of frequency points, thanks to unwieldy analog filters in the legacy equipment. To address this problem, a digital radiometer is under development that can provide noise or spectrum power measurements traceable to NIST thermal noise standards [11]. Noise diodes can then be calibrated as transfer standards at fine frequency resolution to further extend traceability to deployable sensors.

The digital radiometer provides the start of a path toward quantifying uncertainties caused by spectral growth in spectrum sensing measurements. Much of the postulated traceability path is relatively straightforward, but the practical implementation needs to be systematic. For example, the uncertainty propagation needs to be tracked rigorously to ensure an unbroken traceability path. Making spectrum sensors become traceable to common fundamental standards helps to ensure the performant sensor networks, and improves the integrity of spectrum sharing and coexistence measurements.

2) Sensor receiver measurements: The physical core of a spectrum sensor node is a receiver. For this purpose, software-defined radios (SDRs) are popular choices, particularly in prototyping and research. Their appeal is in their low cost, flexibility, and reduced need for hardware engineering.

The benefits of SDRs create a temptation to neglect their physical limitations. Unlike test equipment, for example, significant shielding needs to be added to the SDRs, as well as preselect filters. Without these, bench-top laboratory measurements of ROCs or confusion matrices fail to capture false positives in the field caused by electromagnetic interference (EMI) and out-of-band interferers. Some non-idealities can be corrected by *in-situ* corrections with digital signal processing, although calibration measurements would be required. New "blind" techniques can perform noise figure measurements even if a sensor provides only processed or non-physical data [12].

3) Radiated sensing measurements: These receive less attention, but the knowledge of sensor antenna pattern and directivity can further give insights into absolute gain levels and orientation dependence for link-layer analysis. Wireless standards have quietly (and with no clear definition) started to characterize incident field strength in terms of the power response of an isotropic probe antenna. We proposed a more complete definition [13] for this parameter, which refer to as equivalent isotropic incident power (EIIP). Tests for sensor response to EIIP require a calibrated transmit antenna and calibrated levels of transmit power. These tests are especially necessary when antennas are integrated into the sensor and inseparable from the receiver. Calibration techniques and other test methods are so far not standardized, and performed *ad-hoc* according to the judgment of the tester.

4) Ensemble measurement requirements: Together, the measurements require a plethora of measurement abilities; scattering parameter measurement, electronic noise measurement, power, and antenna pattern and gain, among others. Further, the hardware reconfigurability of SDR-based sensors adds the complexity through a potentially large parameter space of device configurations. For example, automatic gain control can significantly impact the characteristics of the receiver. Calibration challenges for the SDRs scale up with the number of software-configurable radio parameters in the sensor.

III. Characterization of Emissions

A key challenge in developing spectrum sensing algorithms is characterizing emissions in the band of interest. Although it is possible to carry out early-stage algorithm development with simulated data, there are often many aspects of real-world systems that are not easy to model, e.g., out-of-band emissions from real radio frequency (RF) hardware, complex power control and scheduling dynamics, and wireless propagation under realistic conditions.

Empirical characterizations of device emissions can be done either with field or laboratory-based measurements. Field measurements are particularly well suited to capturing realistic variations in aggregate emissions or propagation conditions. However, field measurement campaigns generally suffer from the drawbacks associated with passive observational studies, e.g., uncontrolled emission prevalence, uncontrolled emitter settings, and unknown ground truth information. These drawbacks limit the generalizability of conclusions from field studies. Furthermore, due to the significant costs associated with calibrated RF measurement in the field, many field measurement campaigns instead rely on device-reported data. The accuracy of device-reported data is generally unknown since almost all commercial emitters are uncalibrated. Thus, when planning a field-based emissions measurement, the limitations of observational studies and the required level of measurement accuracy should be considered.

Although it is difficult for laboratory measurements to fully reflect realistic variations in field deployments, and it can be challenging to set-up well-controlled test automation and data collection, laboratory-based emission characterizations have several advantages compared to field observations. First, equipment calibrations tend to more easily yield quantifiable uncertainties in laboratory settings. Second, carefully controlled laboratory conditions and settings help to enable rigorous statistical inference (i.e., the cause of an observed effect can be determined). Third, application of principles of statistical experimental design [14] helps to test a wider range of conditions more quickly compared to field work. Because modern communication systems have many potential configuration settings for the user equipment and network (e.g., power control type, scheduling algorithm), and because there are a wide range of relevant use-cases (e.g., due to different network loading and propagation environments), there are thousands of potential scenarios. One way to address the challenge of a large number of potential settings is through factor screening experimental designs, e.g., the long-term evolution (LTE) uplink emissions factor screening study in [15].

IV. Applications in Uncoordinated Spectrum Sensing for Unlicensed Bands

To start, we focus on large scale WLAN and cellular coexistence in the unlicensed bands. Here, distributed sensing algorithms for WLAN include distributed coordination function (DCF) and enhanced distributed channel access. Meanwhile, 4G LTE license-assisted access (LAA) and 5G new radio unlicensed employ listen before talk (LBT) algorithms. All of these schemes rely heavily on physical channel sensing, such as energy detection and feature detection.

In this domain, sensing follows a process like that of Fig. 2(a) to implement opportunistic transmission using a contention backoff mechanism. In carrier-sense multiple access schemes with collision avoidance, the sensing performed by each transmitter is known as clear-channel assessment. If this indicates that the channel has been available for a protocol-specified delay, the user may transmit in the channel for a duration specified by the protocol. Thus, sensing performance in unlicensed bands relates closely to network performance.

Typically, DCF and LBT schemes try to minimize the chance of transmission collisions by imposing a reasonably accurate channel sensing. Yet, when cellular and WLAN share channels, the channel sensing performance may not map directly to the network characteristics like sum throughput. Heavy frequency re-use in multi-cell multi-tier access scenarios may impose tradeoffs between sensing accuracy and interference tolerance. Over-sensitivity to SOIs blocks transmission opportunities in both cellular small cell and WLAN systems without any interference benefit. Tolerating a moderate collision rate instead can increase the transmission opportunity of nodes which are far apart, and in turn improve the network throughput. Recently, [16] studied this problem in a multi-cell two-tier RAT network. MIMO transmissions provide benefit of enhanced throughput and more robustness against interference. Design and optimization of spectrum sensing schemes for MIMO multi-cell coexistence scenarios deserve a thorough investigation in the future work.

The close connection between sensing and network performance suggests that careful testing of sensing is an opportunity to help ensure robust network performance. Yet, sensing conformance tests are largely neglected in standards. Recent WLAN protocols [17] specify energy detection with a threshold of -62 dBm/20 MHz (defined relative to receiver sensitivity), yet there is no conformance test. Sensing performance measurements are thus only encapsulated in higher-level tests, e.g., for coexistence. Cellular standards [18], meanwhile, provide only a brief 4-line outline of a conformance test for a missed detection rate below 10% at -72 dBm/10 MHz.

V. Applications in Coordinated Spectrum Sensing for CBRS

Spectrum sharing in CBRS is designed to protect incumbent users, who operate ship-borne radar, from entrant users, who generally operate wireless networks. The entrants, known as CBRS devices (CBSDs), comprise two tiers of users: licensed priority access users, and general authorized access users who must vacate spectrum for either incumbent or priority access usage. Channel access for CBSDs in coastal areas is arbitrated by geographical area with a database-driven spectrum access system (SAS). Access decisions, in turn, are driven by real-time incumbent channel occupancy readings collected by an environmental sensing capability (ESC) network.

The design and deployment of an ESC network present competing performance concerns. Most important is to maintain a low false-negative rate to protect incumbents from interference. To support CBSDs, an ESC can maximize channel availability by minimizing false positives. Careful binary detector design can help to reduce both, but at the limit of detector design performance, tradeoffs between rates of false negatives and false positives are unavoidable.

To mitigate self-interference between the deployed CBSDs and ESC nodes, the geographic density of CBSDs has been limited [19]. The SAS must ensure that the aggregate mean interference level from all CBSDs in the neighborhood (a 40 km or 80 km radius) of each ESC node does not exceed -109 dBm/MHz. This is important enough that SAS must account for interference impacts on each ESC node when granting access to CBSDs.

Physical measurements can support the design, optimization, and validation of an ESC network. Measured incumbent and CBSD signal parameters are needed to design and tune sensor nodes to minimize the false positive rate at an acceptably small false negative rate [20]. This has led to measurements of spectrum occupancy and incumbent waveform characteristics, e.g., [21]–[23]. Spectrum regulation and network optimization require data on each node's missed-detection and false-alarm rates. The first laboratory tests for false negative rates for incumbent protection tests check for a 99% detection rate (a 1% false-negative rate) for incumbent activity at sensitivity -89 dBm/MHz. Industry standards [24] have tentatively adopted tests proposed by regulators [25].

Tests proposed so far do not capture false positives in the ESC. Causes include in-band emissions from LTE networks [10], which may be mitigated by ESC detector [20] and antenna design, as well as out-of-band emissions from adjacent-band radars, e.g., [22], [23], [26]. Another possibility, false positives triggered by commercial weather radar, was studied in [27]. Mitigation with RF filters in these legacy radars may be challenging to implement, because of the burden of performance verification. Another ongoing barrier to detecting these incumbent systems is the scant public waveform parameters that are available due to their military use, especially for classified adjacent-band systems.

Infrastructure for CBRS is early in deployment, so large-scale field validation measurements of ESC sensors, sensor networks, incumbent false-positive or false-negative detections, or overall CBRS interference protection have not yet been performed. Measurements will require careful data collection with the ability to separate CBSDs and incumbent waveforms.

VI. Conclusion

Many challenges remain to be addressed to continue improving the dynamism of access for more efficient spectrum use. We have considered CBRS and spectrum commons applications here, but other surveys such as [28] have pointed to this problem elsewhere as well. Coexistence performance testing will therefore only become more challenging.

The application-specific challenges that we presented here suggest that unresolved problems in measurement approaches are an impediment to their utility in spectrum sensing operation. Confusion matrices and ROC curves are taken to summarize detection performance. Even for these simple summary parameters, there are no consensus measurement methods to ground simulated parameters in fundamental physical metrology. While these parameters have clear intuitive meaning, their applicability to system modeling is unclear. Spectrum sensing in the spectrum commons (Section IV) and centrally coordinated sharing (Section V) both involve complex mutual interactions between spectrum users. Sensor measurements that are straightforward with coaxial interconnects can become extremely difficult when sensing and transmission are packaged together into a wireless networking chip, as is normal in mobile devices. Is enough information still accessible for measurements-based "ground-up" models of spectrum sharing performance models, or will data-driven models of high-level network performance marginalize physical measurements?

The large number of combinations of different input variables in a measurement can easily result in an untestably large number of possible test conditions. These could include many combinations of a receiver's selectivity in time, space, frequency, and code, different channel propagation and noise characteristics including correlations between communication and sensing channels, and a protocol parameters for each user. A small, tractable subset of this parameter space needs to be identified in order to make measurements tractable. Can a general procedure be defined to help downselect test conditions with the support of system and coexistence models?

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