A Signal-Processing Perspective on Signal-Statistics Exploitation in Cognitive Radio

Chad M. Spooner[1] and Nilesh V. Khambekar[2]

[1]NorthWest Research Associates, Monterey, CA, cmspooner@nwra.com
[2]The State University of New York, Buffalo, NY, nvk3@buffalo.edu

***Abstract*—Future cognitive radios will require use of both established emitter databases and local spectrum sensing to optimize their performance. We view these techniques as ways of estimating an RF environment map (RFEM), which characterizes the position, directivity, power, and modulation type of all relevant RF emitters in a geographical region of interest. Cognitive radios will make their best decisions when they have the best RFEM information available. Good RFEM estimates are facilitated by spectrum-sensing algorithms that exploit the complex statistics of modern communication signals rather than relying on simplistic energy detection. We illustrate some of the ways that such statistics can be exploited using *collected* modern communications signals.**

***Index Terms*—Cognitive Radio, Spectrum Sensing, Radio-Frequency Environment Maps, Cyclostationary Signal Processing, Spectrum Management, Statistical Signal Processing.**

I. Introduction

As cognitive radios (CRs) and CR networks (CRNs) continue to mature and deploy, they will add their energy to the RF bands they inhabit, which will further complicate their basic task of identifying and utilizing unused-but-assigned portions of the spectrum. CRNs will have to rapidly identify primary user's signals as well as identify and avoid interfering with secondary network signals. This will be done using a mixture of CR-based spectrum sensing and database lookup. We view the database and sensing approaches to RF environment characterization (RFEC) as complementary rather than competitive. Databases will not be updated sufficiently rapidly and cannot be expected to cover all propagation and interference situations adequately. On the other hand, sensing is relatively expensive and is vulnerable to propagation-based impairments such as frequency-selective fading and shadowing.

Emitter databases and CR-based spectrum sensing are both used to enable the CRN to make the best possible decisions regarding all of the CR's adjustable parameters. If the CRN had perfect knowledge of the RF environment, decision-making could be optimized. In this paper we introduce an *RF environment map (RFEM)*, a multidimensional characterization of RF emitters and the opportunities for secondary network access. Our RFEM is focused on spectrum sensing, in contrast to other maps that focus on building and distributing network-related databases [1]. We view emitter databases and local spectrum sensing as resulting in imperfect estimates of an RFEM. It follows that sensing methods should be evaluated in terms of their ability to accurately produce the needed RFEM elements. Our position is that this requires sophisticated exploitation of the statistical structure of all of the involved signals, and that current research and development in CRNs typically underutilizes the available statistical information contained in the primary and secondary signals.

The remainder of this paper is organized as follows. In Section II, we discuss the underutilization of signal statistics found in the open literature, and in Section III we define and discuss the RFEM. Examples of algorithms that exploit more than the energy of the received signal for the purpose of building an RFEM are presented in Section IV, and conclusions are drawn in Section V.

II. Underutilization of Signal Statistics

The vast majority of papers written on the topic of spectrum sensing for CR employ some form of energy detection (ED) to distinguish between the two basic situations of signal-present and signal-absent. ED has universal applicability because all signals possess energy. However, it is well known to suffer performance degradation when the noise power is not known accurately or is variable, the propagation channel is harsh, or cochannel (inband) interference is present [9]. Moreover, ED has severely limited capability to distinguish between different modulation types, and so cannot be used to classify the signals inhabiting the bands of interest.

The provided justification for this widespread and persistent use of ED is simplicity. For example, the recent peer-reviewed papers on spectrum sensing for CR in [2]–[7] all use ED, and provide statements such as "Since noncoherent energy detection is simple ... we will adopt it," "Compared with the cyclostationary detector, the proposed [ED] detector has less computational complexity and ... [is] ... more mathematically tractable," "... due

This paper is based on "Spectrum Sensing for Cognitive Radio: A Signal-Processing Perspective on Signal-Statistics Exploitation", by C. M. Spooner and N. V. Khambekar, which appeared in the proceedings of the International Conference on Networking and Communications, 2012, Maui, Hawaii, January 2012. Manuscript received March 1, 2012, accepted for publication March 27, 2012.

doi:10.4304/jcm.7.7.567-574

to its low computational ... complexities and its fast detection ability, ED is widely employed." So in general, popularity and simplicity are favored over potentially large performance gains. This strikes us as reasonable for product development, but not so reasonable for advanced academic research.

In addition to favoring ED, the complex non-Gaussian statistics of communication signals are often ignored or simply defined away. For example, in [6], random processes that make up a wideband signal's subbands are defined to be Gaussian. In other cases, the signal to be detected is explicitly defined to be non-Gaussian, but is otherwise not statistically specified [8], to enable the use of non-cyclic higher-order cumulants.

Blind signal detection, classification, and parameter estimation can be performed by properly exploiting the statistics exhibited by communication signals [11], which are ignored by ED. Almost all communication signals are *cyclostationary* signals, which means they have one or more nth-order moment functions that are periodic or almost periodic in time for $n \geq 2$ [13]. The presence and harmonic structure of the periodicities as a function of n provide a "digital DNA" for modulation classification and noise-and-interference-tolerant presence detection [11], [14].

A major conceptual and computational difficulty inhibiting widespread use of cyclostationary signal processing is that modern signals possess a very rich and complex harmonic structure starting with $n = 2$ [14]. This is in contrast to the cyclostationary structure of textbook modulation types, such as BPSK, MSK, and CPM, which possess a simple and sparse structure [15]. Our position is that each signal's structure must eventually be more fully exploited to allow significant advances in autonomous CR spectrum sensing and decision making.

For example, consider the textbook BPSK signal. That is, BPSK with independent and identically distributed symbols, square-root raised-cosine pulse function, and zero symbol-clock jitter, phase noise, and carrier frequency drift. The statistical structure of this BPSK signal is simple in that it has exactly five cycle frequencies: $\{0, f_{sym}, 2f_c - f_{sym}, 2f_c, 2f_c + f_{sym}\}$. The measured spectral correlation is shown in Figure 1, where the five features are clear. It is sometimes more convenient to view such functions edge-on, as in Figure 2, where the viewing angle is parallel to the frequency axis.

Another important textbook signal is Gaussian minimum-shift keying (GMSK), which is a component modulation used in GSM. The three-dimensional and edge-on spectral correlation plots are shown in Figures 3 and 4, respectively. This signal has only two significant cycle frequencies, which are given by $2f_c \pm f_{sym}$.

However, these textbook signals are rarely, if ever, used *per se*. Instead, they are used as *components* in more complex signals, such as GSM and OFDM. These more complex signals have a very different set of second-order statistics. For example, GSM has the second-order statistical structure shown in Figures 5 and 6, in which the two

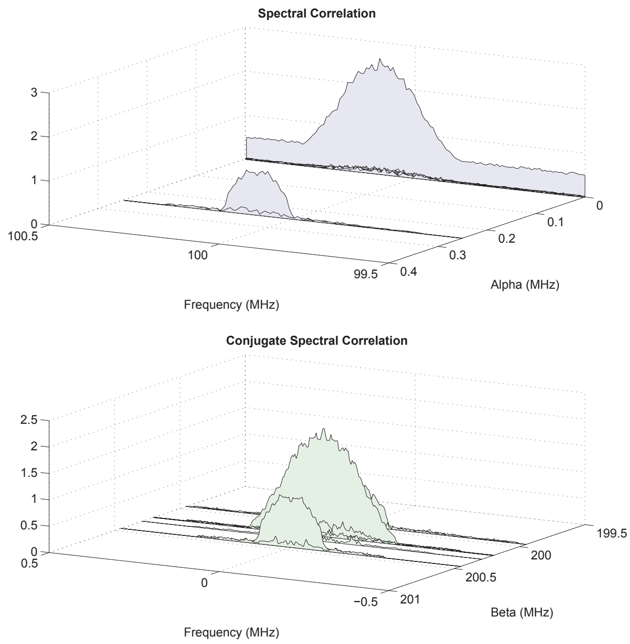


Fig. 1. Measured spectral correlation function for a textbook BPSK signal. The symbol (bit) rate is 0.25 and the carrier offset is 0.1 (normalized frequencies).

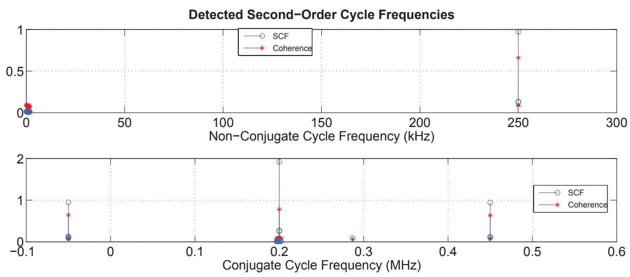


Fig. 2. Measured spectral correlation function for a textbook BPSK signal. The symbol (bit) rate is 0.25 and the carrier offset is 0.1 (normalized frequencies).

conjugate peaks arising from GMSK are visible, but so are many hundreds of additional—potentially exploitable—cycle frequencies.

Two notable recent papers that embrace the statistics of real-world primary-user signal types are [16] and [19]. The former combines cooperative multiple-sensor detection with exploitation of cyclostationarity and compares the obtained performance to ED, while the latter reveals the connections between multitaper spectrum estimation [20] and the theory of spectral correlation [17].

III. The Radio-Frequency Environment Map

The demand for RF spectrum with good propagation characteristics is rapidly increasing in order to support new wireless services, broadband applications, and mobile broadband. Since the RF spectrum is already allocated, we need new spectrum management mechanisms that will make efficient use of the spectrum resource.

Here, we describe two primary approaches for recovering the underutilized spectrum while respecting the

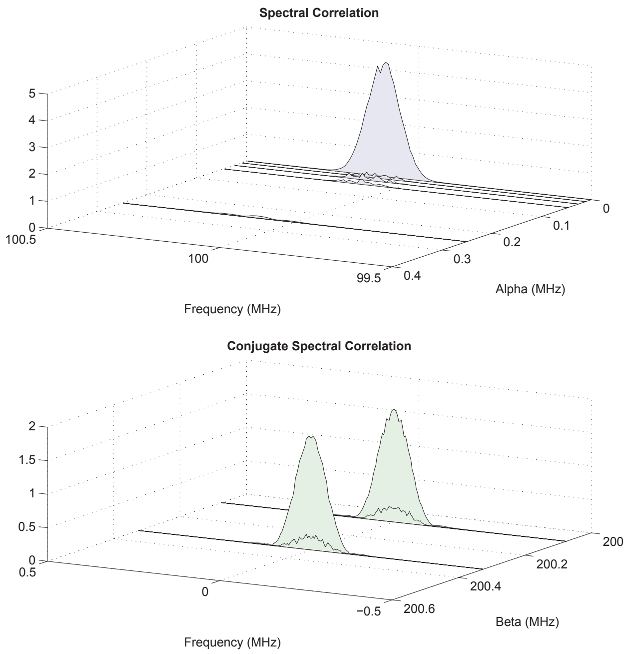


Fig. 3. Measured spectral correlation function for a textbook GMSK signal. The symbol (bit) rate is 0.25 and the carrier offset is 0.1 (normalized frequencies).

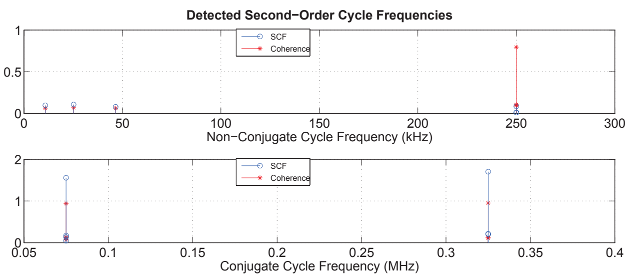


Fig. 4. Measured spectral correlation function for a textbook BPSK signal. The symbol (bit) rate is 0.25 and the carrier offset is 0.1 (normalized frequencies).

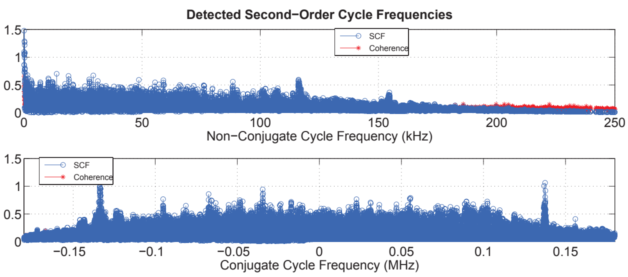


Fig. 5. Measured spectral correlation function for a collected GSM signal.

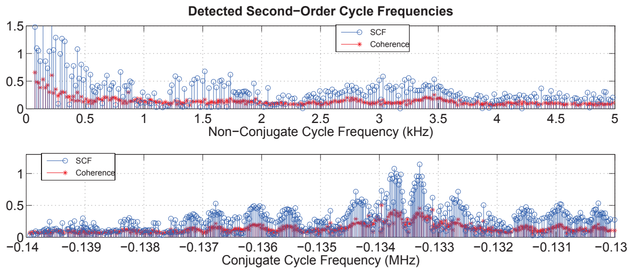


Fig. 6. Measured spectral correlation function for a collected GSM signal.

spectrum rights of the incumbents [21].

1) **Spectrum overlay:** It allows secondary access to the spectrum only when the licensed user is not using the frequency band. The spectrum overlay approach requires secondary transceivers to detect the presence of the signal of the licensed emitter.
2) **Spectrum underlay:** It allows secondary access even when licensed system is in operation. In order to avoid harmful interference, the transmit power of the secondary transmission is constrained to lie below the noise floor.

These approaches do not attempt to make optimal usage of the spectrum. In order to make optimal usage of the spectrum, the interference margins[1] need to be maximally utilized. Unlike spectrum underlay, the secondary power is not constrained below the noise floor. Also, contrary to the spectrum overlay approach, secondary operation is permitted in a frequency band without spatial or temporal constraints. Fig. 7 illustrates secondary usage of the licensed spectrum utilizing the interference margins at the receivers.

Following are some of the challenges for maximizing the secondary usage of the spectrum.

- ***Recovering Spectrum Underutilized by Primary Users.*** The knowledge of location, transmit-power, and radiation pattern for primary-user emitters is necessary for maximizing the recovery of underutilized spectrum. Also, knowledge of the temporal spectrum-usage behavior of primary users is needed to maximize recovery in the temporal dimension.
- ***Optimizing the access to the secondary spectrum.*** In order to maximize the utilization of recovered spectrum, the transmit-power and radiation pattern of the secondary transceivers need to be dynamically controlled. By characterizing the spatial distribution of RF-power, it is possible to detect and quantify the spatial RF-footprint of a network's emitters and thereby provide a path to noninterference with that and other networks.
- ***Reducing the Impact of RF-Propagation Uncertainty.*** RF propagation is not deterministic and uncertainty cannot be avoided. Hence, it becomes necessary to allocate large spatial buffer zones based

[1] Interference margin at a receiver represents the interference power constraint for successful reception of the signal.

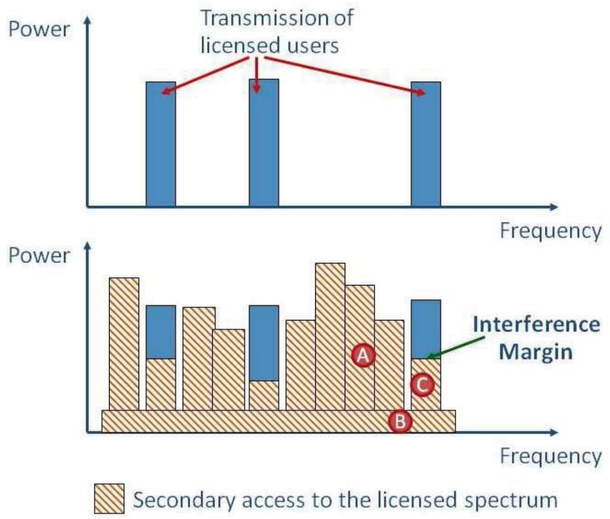


Fig. 7. Maximizing the secondary usage of the licensed spectrum. The top part shows a range of frequency bands and the activity of the licensed emitters. The bottom part shows secondary access to the spectrum while ensuring non-interference to the primary receivers. It exploits the opportunities when licensed emitter is inactive. Such an example secondary spectrum usage is marked with 'A'. The secondary usage is not constrained below the noise floor, similar to the underlay spectrum usage labeled with letter 'B' but the secondary users can exercise higher transmit power depending upon the interference margin at the receiver similar to the secondary spectrum usage marked with 'C'.

on the worst-case path-loss exponent and worst-case shadowing in order to accommodate the uncertainty. Spectrum sensing can be used to gain knowledge about the RF-environment such as shadowing and path-loss variances, which can be used to minimize the spatial buffers needed to mitigate RF-propagation uncertainty.

The RF-environment for a radio is influenced by the positions and radiation patterns of the transceivers, the propagation channels, and noise. The main challenge for RFEC is to obtain the knowledge of the RF environment with bounded inaccuracy under conditions of cochannel interference, channel effects like large-scale path loss, shadowing and multipath, and transceiver mobility.

If we always knew the exact values of the parameters influencing the RF environment, it would be possible to make optimal use of the underutilized spectrum. From the perspective of desiring maximum recovery of the underutilized spectrum and maximum utilization of the recovered spectrum, we propose following two spatial quantities:

1) **Occupancy** represents the aggregate RF power received at a point in space for a particular band of frequencies. The occupancy value at a point captures the sum effect of transmit-power, radiation pattern, and position of all emitters, as well as channel effects and noise.
2) **Opportunity** represents the margin for interference power at a point from a particular direction. In the case of omnidirectional reception, there is a single opportunity value associated at each point which represents margin for inclusion of additional interference power.

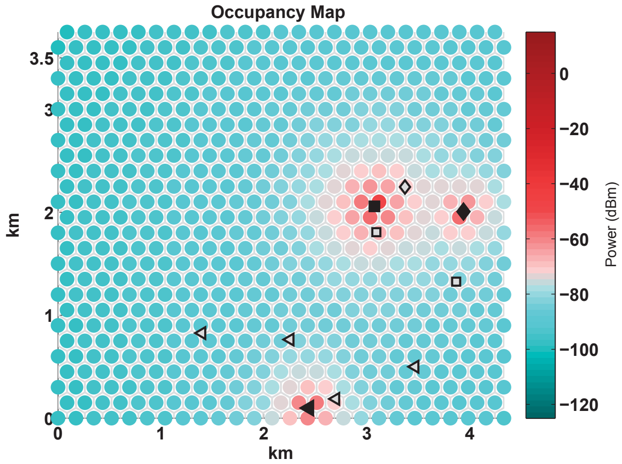


Fig. 8. Single-band occupancy map showing the aggregate RF power for unit area cells. Emitters and receivers in a single network have the same shape; emitter is solid.

The occupancy and opportunity attributes are based on the physical interference situation. The spatial distribution of occupancy and opportunity is captured by the *Occupancy* and *Opportunity Maps*. Based on characterization of occupancy and opportunity, it is possible to make decisions about connectivity and RF routes between any two points in space. We capture this connectivity information through use of the *Connectivity Map*. The connectivity map can be generalized to show multiple channels. Taken together, the proposed occupancy, opportunity, and connectivity maps comprise the RFEM. Figures 8–10 illustrate the three constituent maps with a setup of three networks operating in a single spectral band.

A multi-band version of the connectivity map is shown in Figure 11 to illustrate its potential application to multi-network multi-band spectrum planning and dynamic management.

IV. Exploitation of Signal Statistics

The ultimate goal of signal-statistics exploitation for CR is to blindly estimate the RFEM. In this short paper, we illustrate how exploitation of *small subsets* of second-order statistics can be used to detect, geolocate, and characterize multiple cochannel signals. To emphasize the real-world applicability of exploitation of signal statistics, we use a three-signal scenario in which two of the signals are collected. In particular, we consider an RF scene involving collected ATSC-DTV and WCDMA signals together with a simulated AM-DSB signal. A version of the scene with low signal-to-noise ratio (SNR) is depicted in Figure 12. In this scene, the inband SNR for the DTV and WCDMA signals is about -18 dB, whereas for the AM signal it is about -14 dB.

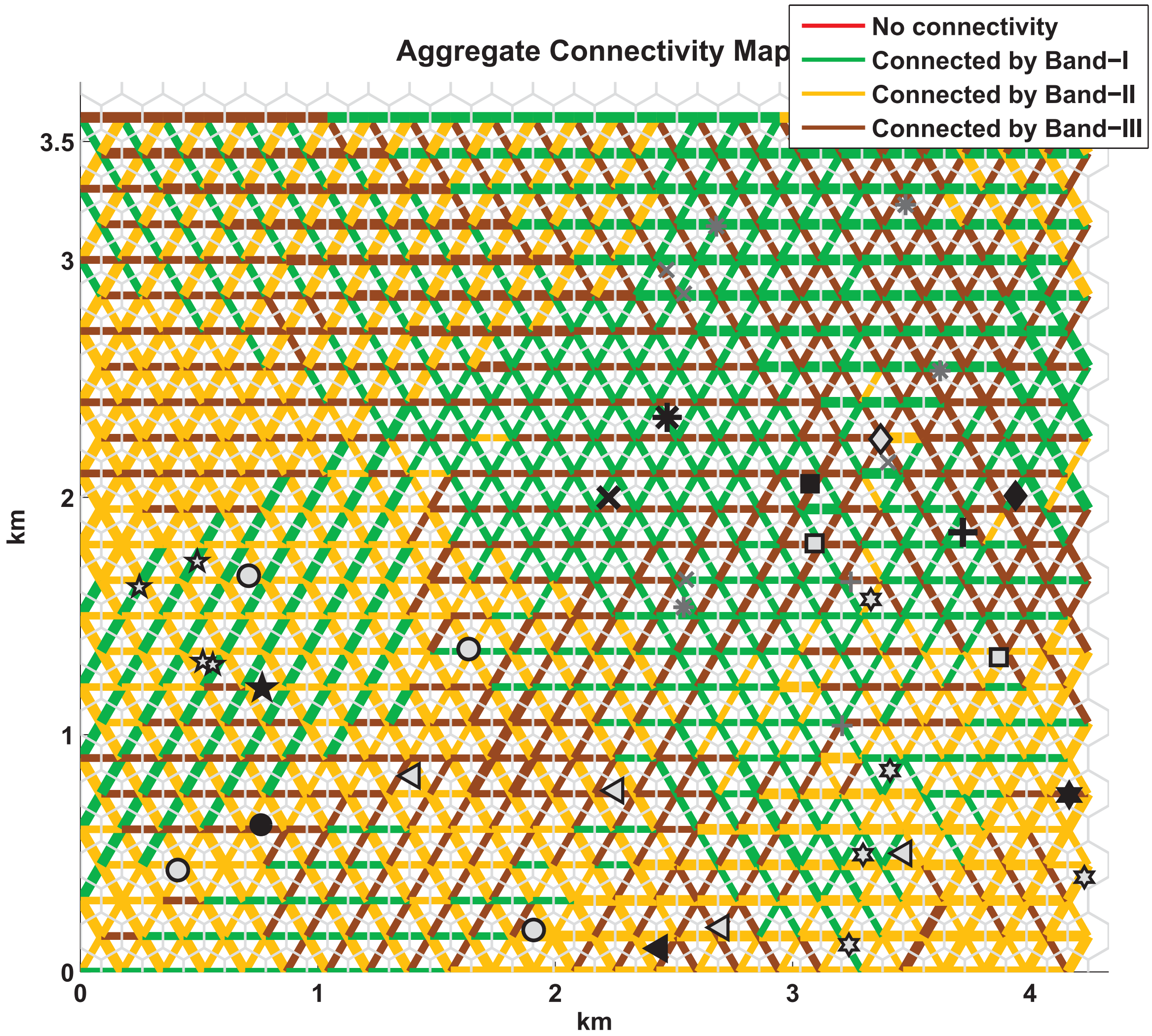


Fig. 11. Multiple-band connectivity map showing the degree to which adjacent unit area cells can connect using a new radio link. Transmitters and receivers in the same network have the same shape; the transmitter is solid. The particular frequency band is encoded through the color of the connecting lines, and the line color is determined by the best available connectivity. This kind of map reveals exploitable spectrum holes in the spatial and frequency dimensions. For this particular set of networks, the spectrum holes for band I (green), band II (yellow), and band III (brown) are easily discerned. Moreover, the directivity of the transmitters is taken into account, so that the best channel to use depends on the spatial orientation of the to-be-added transmitter-receiver pairs.

We consider detection, geolocation, and power-estimation for each of the three signals in the scene.

A. Detection

For signal detection, we exploit the second-order statistics of each signal through the spectral correlation function (SCF) [17] evaluated at one or two cycle frequencies (CFs). For the WCDMA signal, we assume knowledge of its chip rate CF of 3.84 MHz, for the DTV signal we assume knowledge of its carrier frequency and basic symbol rate (10.7622 MHz) to compute the values of its two CFs, and for the AM signal we assume knowledge of its doubled-carrier CF.

The detection algorithm is a suboptimal noncoherent cycle detector. This structure integrates the magnitude of the SCF for one or more CFs and sums the result. As such, it does not use detailed knowledge of the signal's SCF, only its CFs. Mathematically, let $x(t)$ denote the received noisy three-signal RF scene for $t = 0, 1, \ldots, T-1$, and consider a target CF of α_*. Then the detection statistic is given by

$$Y_{scd} = \sum_k \left| \hat{S}_{x_T}^{\alpha_*}(f_k) \right|^2, \tag{1}$$

where $\hat{S}_{x_T}^{\alpha_*}(f)$ is the cyclic periodogram [17].

We consider the hypothesis testing problem given by

$$\begin{aligned} H_1 :& \quad x(t) = s_*(t) + pi(t) + n(t), \\ H_0 :& \quad x(t) = pi(t) + n(t), \end{aligned} \tag{2}$$

where $s_*(t)$ is the signal to be detected (one of the three signals in the scene), $i(t)$ comprises the other two signals, $n(t)$ is WGN, and p controls whether the the interference is considered in the hypotheses. When p is zero, the

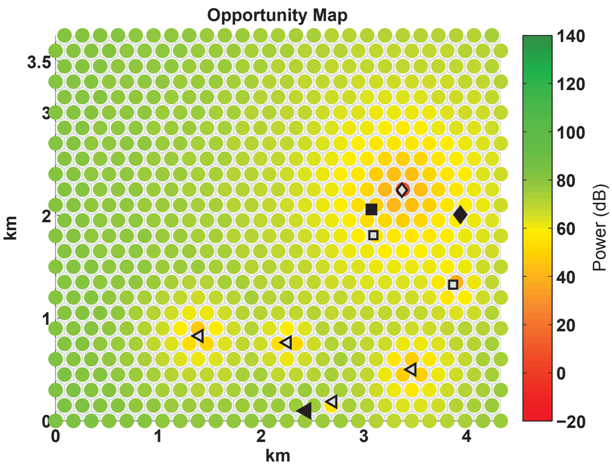


Fig. 9. Single-band opportunity map showing the RF power that each unit area can tolerate given the presence of the shown networks. High-opportunity regions are green; low are red.

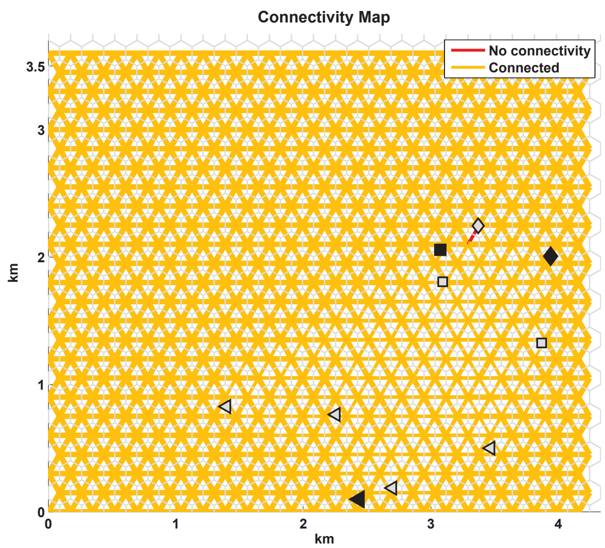


Fig. 10. Single-band connectivity map showing the degree to which adjacent unit area cells can connect using a new radio link. Two adjacent unit areas are not connected if the opportunity value at either unit area is below the minimum required signal-to-interference-and-noise ratio (SINR). Unit areas that cannot be connected are joined by a red line. The ability to connect two unit areas is encoded into the width of the line connecting their centers.

detection performance relates to detecting a signal in noise, whereas when it is one, the performance relates to detection in the presence of both noise and interference.

The detection performance for the RF scene in Figure 12, which includes two collected signals, is provided in Figure 13 for $T/f_s = 5$ ms. Detecting each of these three signals in the presence of noise only is quite easy for this block length, and is only slightly more difficult when interference is also present on the two hypotheses. We emphasize that the two wideband signals are collected,

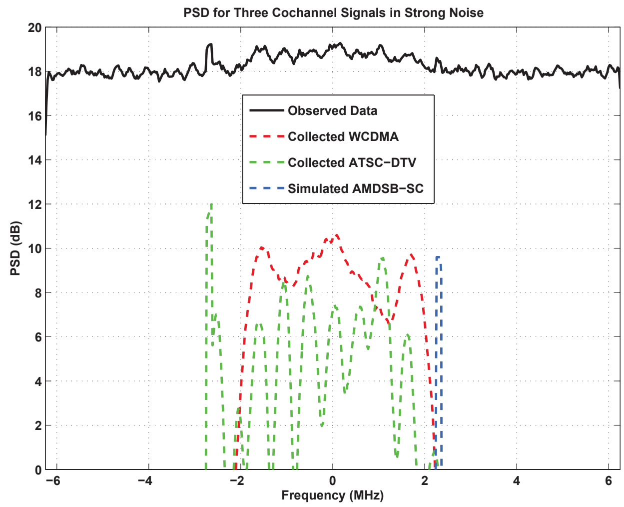


Fig. 12. Low-SNR three-signal RF scene. We note that the WCDMA and DTV signals are collected using a Tektronix RF Hawk receiver and a custom data acquisition system employing ADC at 12.5 MHz (complex) with resolution 14 bits/sample. The action of the unknown propagation channel is particularly evident for the DTV signal, which ideally has a flat spectrum over 6 MHz.

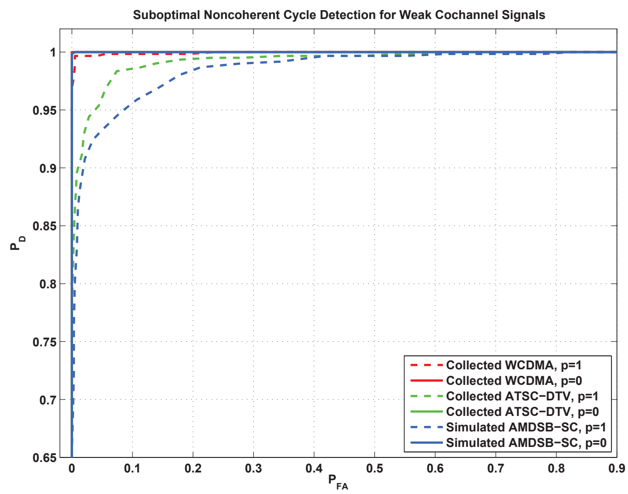


Fig. 13. Receiver operating characteristics for detection of each of three cochannel signals. 800 ms of data was processed using 5-ms blocks. The detection statistic for noise alone is much smaller than that for either (1) all three signals present, and (2) signal of interest absent but interference signals present. It is relatively easy to detect the presence of any of the three signals regardless of the presence or absence of the other signals.

not simulated, and are subject to random channel effects and other impairments as shown in the individual-signal PSDs of Figure 12.

B. Power Estimation

In this section we demonstrate that the power levels of the weak signals in our RF scene can be accurately tracked using small block lengths in spite of cochannel interference. Consider a unit-power signal $s(t)$ with SCF $S_s^\alpha(f)$. The SCF for $As(t)$ is simply $|A|^2 S_s^\alpha(f)$, which suggests a simple least-squares estimation problem for A.

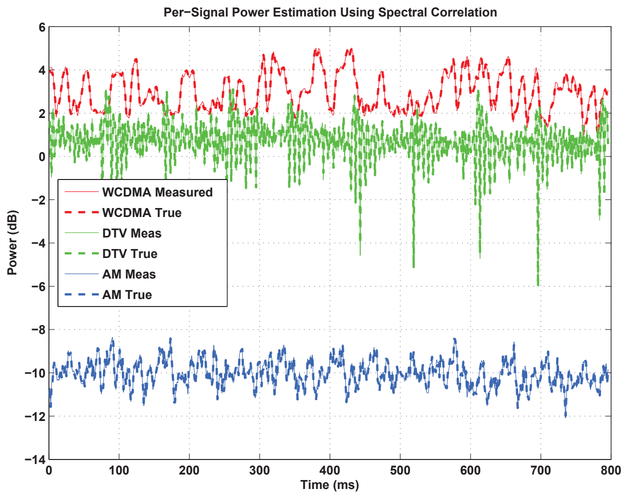


Fig. 14. Per-signal power estimation for each signal in the three-signal RF scene of Figure 12 using 5-ms blocks. The estimated and true curves are nearly identical for each signal.

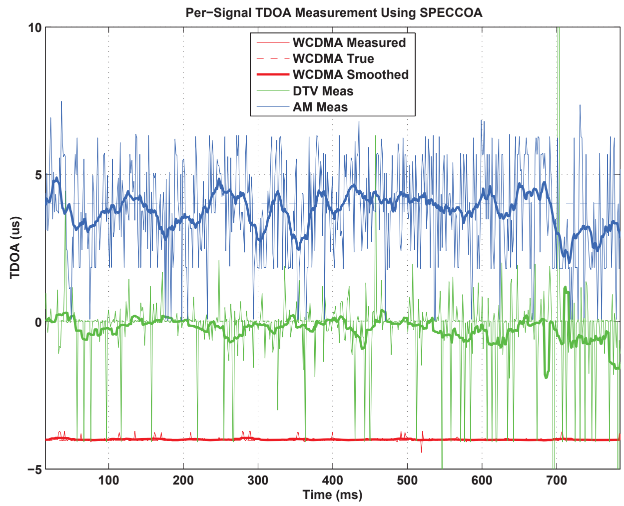


Fig. 15. TDOA estimation performance for the three-signal RF scene of Figure 12, but with reduced noise level, and using the same 5-ms blocks as in the detection and power-estimation examples.

The resulting estimator is given by

$$\left|\hat{A}\right|^2 = \frac{\left|\sum_k \hat{S}_{xT}^{\alpha_*}(f_k) S_s^{\alpha_*}(f_k)\right|}{\left|\sum_k S_s^{\alpha_*}(f_k)\right|}. \quad (3)$$

The results are shown in Figure 14, where it is difficult to distinguish the measured values from the ideal values. Note also the evident power-control power variations in the WCDMA signal, which can take on values of 0.5, 1.0, 1.5, and 2.0 dB.

C. TDOA Estimation for Geolocation

In this section we provide evidence that the various emitters in a difficult RF scene can be geolocated through multiple TDOA estimates. The TDOAs are measured using the SPECCOA algorithm [18], which correlates an SCF measurement for one sensor with the cross SCF measurement from two sensors to obtain an estimate of the delay experienced by the signal as it moves past the sensor pair. TDOA estimation is not as tolerant to noise as are detection and power estimation, but performance can be improved by increasing the processing block length. Instead, though, we provide results for the 5-ms block used here but with reduced noise. The RF scene is as in Figure 12 except the noise spectral density is reduced by 20 dB. This leads to inband SINR values for WCDMA and DTV of about -2 dB. The TDOA estimation results are shown in Figure 15. The estimator performance for collected WCDMA is excellent for this SINR and block length, but performance decreases for DTV and the relatively weak AM signal. The figure also shows a temporally smoothed version of the TDOA estimate for each signal, which indicates that accurate estimates can be made of the signal's TDOA provided the sensor can process sufficiently many blocks.

V. Conclusion

We advocate the use of a RF environment map (RFEM) that is obtained and updated through the joint application of central database lookups and local spectrum sensing in cognitive radio (CR) applications. The multidimensional RFEM characterizes the RF environment in a geographical region of interest by capturing the spatial and spectral distribution of occupancy, opportunity, and connectivity. These quantities relate to the aggregate RF power, interference margin, and ability to connect radios at any two points, respectively. Our position is that updating the RFEM in the future will become increasingly difficult as ever more emitters vie for the best spectrum. We advocate increased research and development of signal processing algorithms that can tolerate strong noise and multiple cochannel interferers. We have shown that suboptimal processing structures can provide noise-and-interference tolerant algorithms provided the involved signals' true statistical nature is exploited. Moreover, we have demonstrated these ideas using **collected WCDMA and DTV signals**, which have passed through unknown and time-varying propagation channels and data acquisition subsystems prior to RFEM processing.

We encourage signal processing researchers to develop methods of spectrum sensing for cognitive radio that exploit the rich and complex statistics of today's real-world communication signals. In our future work, we will connect estimator output to RFEM component maps to evaluate the quality of maps that are based solely on spectrum-sensing.

References

[1] Y. Zhao, B. Le, and J. Reed, "Network Support: The Radio Environment Map," *Chapter 11 in Cognitive Radio Technology, Second Edition*, B. Fette, Ed., Academic Press, 2009.

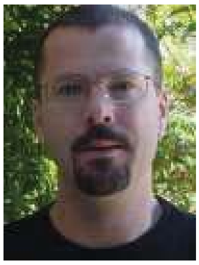
[2] W-Y Lee and I. Akyildiz, "Optimal Spectrum Sensing Framework for Cognitive Radio Networks," *IEEE Trans. Wireless Comm.* **7**:10, Oct. 2008, pp. 3845–3857.

[3] Z. Quan, S. Cui, A. Sayed, and H. Poor, "Optimal Multiband Joint Detection for Spectrum Sensing in Cognitive Radio Networks," *IEEE Trans. Sig. Proc.* **57**:3, March 2009, pp. 1128–1139.

[4] P. Paysarvi-Hoseini and N. C. Beaulieu, "Optimal Wideband Spectrum Sensing Framework for Cognitive Radio Systems," *IEEE Trans. Sig. Proc.*, **59**:3, March 2011, pp. 1170–1182.
[5] Z. Quan, W. Zhang, S. Shellhammer, and A. Sayed, "Optimal Spectral Feature Detection for Spectrum Sensing at Very Low SNR," *IEEE Trans. Comm.*, **59**:1, Jan. 2011, pp. 201–211.
[6] K. Hossain and B. Champagne, "Wideband Spectrum Sensing for Cognitive Radios with Correlated Subband Occupancy," *IEEE Sig. Proc. Letters,* **18**:1, Jan. 2011, pp. 35–38.
[7] Y. Chen, "Improved Energy Detector for Random Signals in Gaussian Noise," *IEEE Trans. Wireless Comm.*, **9**:2, Feb. 2010, pp. 558-563.
[8] W. Jun and B. Guangguo, "Spectrum Sensing in Cognitive Radios Based on Multiple Cumulants," *IEEE Signal Proc. Letters,* **17**:8, Aug. 2010, pp. 723–726.
[9] W. A. Gardner and C. M. Spooner. "Signal Interception: Performance Advantages of Cyclic-Feature Detectors," *IEEE Trans. on Comm.,* **40**:1, pp. 149–159, January 1992.
[10] C. M. Spooner, "Classification of Cochannel Communication Signals using Cyclic Cumulants," *Proc of the 29th Asilomar Conference on Signals, Systems, and Computers,* October 1995, pp. 531–536.
[11] C. M. Spooner, W. A. Brown, and G. K. Yeung, "Automatic Radio-Frequency Environment Analysis," *Proc of the 34th Asilomar Conference on Signals, Systems, and Computers,* October 2000, pp. 1181–1186.
[12] C. M. Spooner, "On the Utility of Sixth-Order Cyclic Cumulants for RF Signal Classification," *Proc of the 35th Asilomar Conference on Signals, Systems, and Computers,* 11/01, pp. 890–897.
[13] C. M. Spooner and W. A. Gardner, "The Cumulant Theory of Cyclostationary Time-Series, Part I: Foundation and Part II: Development and Applications," *IEEE Trans Sig Proc,* **42**, pp. 3387–3429, Dec. 1994.
[14] C. M. Spooner and R. B. Nicholls, "Spectrum Sensing Based on Spectral Correlation," *Ch. 18 in Cognitive Radio Technology, Second Edition,* Ed. B. Fette, Academic Press, 2009.
[15] W. A. Gardner, W. A. Brown, and C-K Chen, "Spectral Correlation of Modulated Signals: Part II—Digital Modulation," *IEEE Trans. Comm.* **35**:6, pp. 595–601, June 1987.
[16] J. Lunden, V. Koivunen, A. Huttunen, and H. Poor, "Collaborative Cyclostationary Spectrum Sensing for Cognitive Radio Systems," *IEEE Trans. Sig. Proc.*, **57**:11, Nov. 2009, pp. 4182–4195.
[17] W. A. Gardner, *Statistical Spectral Analysis*. Englewood Cliffs, NJ: Prentice-Hall, 1987.
[18] W. A. Gardner and C-K Chen, "Signal-Selective Time-Difference-of-Arrival Estimation for Passive Location of Man-Made Signal Sources in Highly Corruptive Environments," *IEEE Trans. Signal Proc.*, **40**:5, May 1992, pp. 1168–1197.
[19] S. Haykin, D. Thomson, and J. Reed, "Spectrum Sensing for Cognitive Radio," *Proceedings of the IEEE*, **97**:5, May 2009, pp. 849–877.
[20] D. J. Thomson, "Spectrum Estimation and Harmonic Analysis," *Proceedings of the IEEE*, **70**:9, Sept. 1982, pp. 1055–1096.
[21] Q. Zhao and A. Swami, "A Survey of Dynamic Spectrum Access: Signal Processing and Networking Perspectives," *Acoustics, Speech and Signal Processing,* **97**:5, April 2007.

ACKNOWLEDGMENT

We thank Professor Octavia Dobre of The Memorial University of Newfoundland for facilitating the invitation to present portions of this work at ICNC 2012. We would also like to thank the reviewers of the original conference paper and this extended journal paper for their careful readings and helpful comments.



Chad M. Spooner received the BS degree from the University of California at Berkeley in 1986, and the MS and PhD degrees from University of California at Davis in 1988 and 1992, all in electrical engineering. Over the past twenty years Dr. Spooner has held research positions at Mission Research Corporation, Statistical Signal Processing Incorporated, Alliant Techsystems, and NorthWest Research Associates. Research sponsors include DARPA, the Naval Research Laboratory, Lockheed-Martin Company, Tektronix, BAE Systems, and IARPA. He is also an Adjunct Research Professor at Virginia Tech and an ocassional lecturer in electrical engineering at the Naval Postgraduate School.

Dr. Spooner's research interests include weak-signal detection and parameter estimation, automatic modulation classification, the theory of the higher-order statistics of communication signals, interference mitigation in satellite communications, spectrum sensing for cognitive radio, and pattern classification for biomedical applications. Dr. Spooner received the 1992 Award for Excellence in Ph.D. Research from the UC Davis Chapter of Sigma Xi and the 1995 UC Davis Allen G. Marr Prize in the Physical Sciences and Engineering for his 1992 doctoral work.

Dr. Spooner has published more than thirty papers in reputable journals, conferences, and technical books. Most recently, Dr. Spooner is co-author of the chapter Spectrum Sensing Based on Spectral Correlation in the 2009 book entitled Cognitive Radio Technology, Second Edition, edited by Dr. Bruce Fette. Dr. Spooner is currently with NorthWest Research Associates in Monterey, California.

Nilesh V. Khambekar is currently a doctoral student at the University at Buffalo, SUNY. He received his Bachelors's degree from Pune University, India in 2001, India and Masters degree from Wayne State University, United States, in 2006. His research interests are dynamic spectrum access mechanisms and cognitive radio systems.