Design and Implementation of Probabilistic Methods for Spectrum Sensing in Cognitive Radios

Stanislav Ivanenko
dept. Information and Network Engineering
National University of Radio Electronics
Kharkiv, Ukraine
stanislav.ivanenko@nure.ua

Andrii Ponomarov
dept. Electrical Engineering
University of Pardubice
Pardubice, Czech Republic
andrii.ponomarov@student.upce.cz

Oleksii Fedorov
dept. Information and Network Engineering
National University of Radio Electronics
Kharkiv, Ukraine
oleksii.fedorov@nure.ua

Valeriy Bezruk
dept. Information and Network Engineering
National University of Radio Electronics
Kharkiv, Ukraine
valerii.bezruk@nure.ua

Jan Pidanič
dept. Electrical Engineering
University of Pardubice
Pardubice, Czech Republic
jan.pidanic@upce.cz

Petr Doleï¿œel
dept. Process Control
University of Pardubice
Pardubice, Czech Republic
petr.dolezel@upce.cz

***Abstract*—The paper deals with new unconventional methods of detecting unoccupied frequency channels in cognitive radios. The main feature of these methods consists in their ability of detecting unknown signals in the presence of noise under the condition of a priori uncertainty. It makes it possible to increase the efficiency of detecting unoccupied frequency channels in cognitive radios due to the fact that these methods track changes in the probabilistic properties of observations. During the course of spectrum sensing of the frequency range, the detected signals are divided into known (classified training samples of which are available in the system) and unknown ones. Application of methods for recognizing specified signals in the presence of unknown signals makes it possible to simultaneously avoid the erroneous occupation of a frequency channel by a secondary user, in the case when previously unregistered signal occurs, and also refresh the cognitive radio database. To detect unknown signals, only information about probabilistic characteristics of the channel noise is used.**

***Index Terms*—Cognitive radio, spectrum sensing, unoccupied channel, detection, secondary user, a priori uncertainty, efficiency**

I. Introduction

Development and modernization of telecommunication networks stimulates an increase in traffic, which in turn acts as an accelerating agent for offering new services. These new services demand development of communication technologies. Wireless technologies have received an exclusive development in recent years. The problematic aspects of wireless communications are: (i) increasing transmission rate; (ii) lack of frequency channels; (iii) low efficiency of frequency resource utilization due to static allocation of frequencies for licensees.

Licensed frequency bands are available for use only to those users for whom they are assigned. However, the radio frequency resource remains limited and its efficient use is realized not for all available frequencies. To improve the efficiency of the frequency resource utilization, a cognitive radio (CR) technology was built. Such a technology allows secondary users to occupy fragments of the frequency band when they are not used by primary users who have the right to use them on a license basis. That is why, when operating wireless networks, it is essential to monitor occupancy of the frequency resource and perform the search for frequency channels which are temporarily vacant, i.e. not used by primary users. Spectrum sensing in cognitive radio networks serves this goal. The aim of the spectrum sensing is to identify signals in distinct frequency channels and divide the operating frequency range into "occupied" and "available" frequency sub-bands.

A literature survey [1]–[5] results in this list of conventional methods for detecting radio emissions of primary users: (i) energy, (ii) matched filtering and (iii) cyclostationarity method.

The energy method requires no prior knowledge about the signal to detect, while the last two rely on some sort of characterization of the signal. The ease of implementation and use of the energy detector are two main factors which have predestined its wide spread. However, at low SNRs this method performs poorly. Also, it suffers from uncertainty in determining the required threshold of operation. The uncertainty is caused by changes of signal and noise environment in frequency channels.

The matched filtering method is capable of delivering short observation times, that is, relatively short input samples are sufficient to ensure specified values of probabilities of false alarm or missed detection. The drawback of the method is the fact it requires a receiver of a particular type to process signals of each class of primary users. This is impractical for CRs.

The cyclostationarity method makes use of the fact that short or long term dependencies must show up in real world modulated signals. An obvious advantage of the method is its ability to discriminate signals from noise reliably. The method does well even in cases when the sought for signals are below the noise level. Among disadvantages of the method are high computational complexity and significant observation time, which is not good from the perspective of the CR as it decreases potential secondary channel throughput.

Judging the pros and cons of the aforementioned methods to detect signals in the context of employing them to classify frequency channels into currently used and free ones we conclude that cognitive radio systems will benefit from relying on unconventional methods of signal detection and recognition. The feature of these methods is that they allow us to reference unknown signals to a special class of signals for which no prior information is provided. Acting this way first makes it possible to refresh the CR database of signals peculiar to a particular frequency band and second fusing the tasks of detection and recognition of sensed signals into one operation creates preconditions for prioritizing access to the frequency resource for secondary users who exhibit receptiveness to possible transmission delays.

The rest of the paper deals with describing ideas put into the basis of unconventional methods for signal detection and recognition and reports results of performance analysis of these unconventional methods applied to real-world samples of signals and noise, obtained during spectrum sensing in CRs.

II. Spectrum Sensing

A. Decision Rules for Blind Signal Detection

We put forward two hypotheses. The first one, H^0 is valid if the frequency band to analyze is empty (i.e. only noise present). The alternative hypothesis, H^1 becomes valid if H^0 fails (i.e. a mixture of signal and noise present).

Peculiarities of application of the theory of signal detection to solving tasks of automated radio monitoring (i.e. spectrum sensing) one may find, for example, in [2], [6]. Let $\vec{X} \sim W(\vec{X}|\vec{\alpha})$ be an observation vector of length L and $W(\vec{X}|\vec{\alpha})$ is a multivariate PDF specified by a vector parameter $\vec{\alpha}$. The following decision rule is applicable to detect unknown signals:

$$W(\vec{X}|\vec{\alpha}^{\,0}) \underset{H^1}{\overset{H^0}{\gtrless}} \Delta^0, \tag{1}$$

where $\vec{\alpha}^{\,0}$ is the vector parameter of the intrinsic distribution of H^0; Δ^0 is a certain threshold value selected to provide the specified probability of false alarm.

If $\vec{X}$ comes from a multivariate Gaussian distribution, then (1) turns to [6]–[8]

$$(\vec{X}-\vec{\mu}^{\,0})^T(\mathbf{R}^0)^{-1}(\vec{X}-\vec{\mu}^{\,0}) \underset{H^1}{\overset{H^0}{\lessgtr}} \Delta^0, \tag{2}$$

where $\vec{\mu}^{\,0}$ and $\mathbf{R}^0$ are mean vector and covariance matrix of the noise. Estimates for $\vec{\mu}^{\,0}$, $\mathbf{R}^0$ are determined from a learning sample of noise $\vec{X}^0$ respectively.

In turn, when for decision-making a set of observation vectors $\{\vec{X}_r\}_{r=1}^{v}$ is used, the decision rule (2) takes the form:

$$\sum_{r=1}^{v}(\vec{X}_r-\vec{\mu}^{\,0})^T(\mathbf{R}^0)^{-1}(\vec{X}_r-\vec{\mu}^{\,0}) \underset{H^1}{\overset{H^0}{\lessgtr}} \Delta^0_v. \tag{3}$$

Another variation of rule (3) is

$$\mathrm{Tr}\,(\mathbf{R}-\mathbf{R}^0)(\mathbf{R}-\mathbf{R}^0)^T \underset{H^1}{\overset{H^0}{\lessgtr}} \Delta^0_{\mathbf{R}}, \tag{4}$$

where $\mathbf{R}^0 = \frac{1}{n_0}\sum_{r=1}^{n_0}(\vec{X}^0_r - \vec{\mu}^0_r)(\vec{X}^0_r - \vec{\mu}^0_r)^T$, $\mathbf{R} = \frac{1}{v}\sum_{r=1}^{v}(\vec{X}_r - \vec{\mu}^0_r)(\vec{X}_r - \vec{\mu}^0_r)^T$, n_0 is for the size of a training sample and $v \ll n_0$ is the size of a control sample; $Tr(\cdot)$ designates the matrix trace operator.

A conventional energy detector is

$$\vec{X}^T\vec{X} \underset{H^1}{\overset{H^0}{\lessgtr}} \Delta^0. \tag{5}$$

The decision rules (2) – (5) define some possible algorithms for detecting unknown signals in the presence of noise, and can be used for determining occupancy of channels in CRs.

B. Selection and Recognition of Given Signals in the Presence of Unknown Ones

The following decision rule [6], which compares the Mahalanobis distance to a threshold, is used to solve the problem of selecting and recognizing given signals in the presence of unknown ones:

$$H^i : \begin{cases} D^i < \Delta^i, \\ D^i \le D^l,\ i,l=\overline{1,M},\ i \ne l; \end{cases} \tag{6a}$$

$$H^{(M+1)} :\quad D^i \ge \Delta^i,\ i=\overline{1,M}, \tag{6b}$$

where H^i is the hypothesis which states the i-th known signal is present. In turn $H^{(M+1)}$ is valid if H^i fails, i.e, an unknown signal have been spotted in the frequency channel. Next, $D^i = (\vec{X}-\vec{\mu}^i)^T(\mathbf{R}^i)^{-1}(\vec{X}-\vec{\mu}^i)$, $\vec{\mu}^i$ and $\mathbf{R}^i$ are the mean vector and covariance matrix of the i-th known signal represented by its training sample and Δ^i is some threshold value.

Decision rule (6) serves the goal of formalizing the problem of selection and recognition of M specified signals and referencing unspecified ones to the $(M+1)$-th class. A stepwise procedure is induced by this rule. Namely, first we test the hypothesis about the i-th specified signal presence. Than, if all the hypotheses H^i have been rejected, we declare the received signal to be unknown one from the $(M+1)$-th class.

C. Spectrum Sensing System

With the aid of a USB DVB-T TV tuner and open-source SDR# application, samples of signals and noise, typical for the IEEE 802.22 standard frequency range, were accumulated. Such a tuner is able to receive radio emissions within the range 24–1710 MHz, yet it can analyze spectra of signals with types of modulation specific to the mentioned frequency range, namely, AM, FM, WFM, NFM, CW, SSB, etc. Control samples of signal and noise realizations of size 1000 were employed for the ensuing analysis of the operating characteristics of the signal detection rules. There were L $\le$ 512 time bins in every realization.

D. Procedure to Determine Threshold Value Δ^0

In this paper, the following procedure of selecting threshold values Δ^0 for rules (2), (3) and (5) was used.

1. Based on the learning sample $\vec{X}^0$, estimates for $\vec{\mu}^0$ and $\mathbf{R}^0$ are found. These values are treated as reference ones.
2. For every testing sample of noise, values of left-hand-sides of decision statistics of rules (2)–(5) are computed.

3. Order statistics $\Delta^0_{(1)}, \ldots, \Delta^0_{(N)}$ are obtained by arranging in ascending order values of decision statistics found in the previous stage of the algorithm. The number of testing samples is designated with N.
4. Threshold Δ^0 is chosen as the order statistic $\Delta^0_{(n)}$, where n is the smallest sequence number such that $1 - \frac{n}{N} \leq \mathsf{P}(1|0)$. Here $\mathsf{P}(1|0)$ means the probability of false alarm.

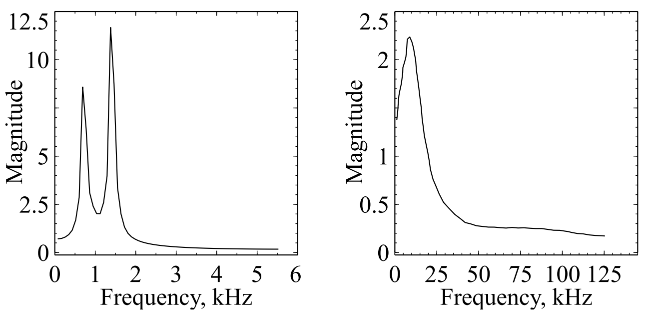
III. Evaluation

A. Operating Characteristics of Signal Detection Rules

Here we present results of performance evaluation of decision rules (2) through (5) in terms of dependency of the probability of channel occupancy correct detection on the signal to noise ratio. The switch from the time to frequency domain is beneficial from the perspective of spectrum sensing in CRs. Such a switch allows us to localize the signal within a frequency sub-band and thereby increase the difference between the mixture of signal+noise and noise itself. In our experiment two types of signals were considered as unknown ones. Namely, a narrow band signal AFS FSK 130 Bd and a wide band WFM signal. Magnitude spectra of these signals are depicted in Fig. 1.

To get probabilities of signal correct detection $\mathsf{P}(1|1)$ in the presence of noise, a series of simulations was performed. At the learning stage, parameters of the decision rules from sub-Sec. II-A were determined with respect to accumulated realizations of noise. Threshold values were selected in accordance with the algorithm from sub-Sec. II-D so as to provide the requested values of the false alarm probability, $\mathsf{P}(1|0) = 0.04$. Probabilities $\mathsf{P}(1|1)$ were estimated as proportions, that is ratios of the number of successful trials to the total number of trials. The total number of trials was 1000. A trial was declared successful if it yielded a correct decision on the presence of unknown signal (AFS FSK 130 Bd or WFM, one at a time).

Fig. 2 depicts detailed information on the behavior of rules (2) through (4) as well as the comparison with a conventional energy detector (ED), rule (5). The dependencies of $\mathsf{P}(1|1)$ vs SNR were obtained under these assumptions: the DFT block size $L = 128$; the number of realizations used to make a decision was $v \in \{1, 2, 3\}$. Note that for $v = 1$ decision rule (3) reduces to rule (2). The leftmost plot in Fig. 2 corresponds to the use of decision rule (3) for testing the hypothesis H^0 against H^1 about the presence of AFS FSK 130 Bd signal. In turn, the last two plots in Fig. 2 show respectively the dependencies peculiar to rules (3) and (4) applied to detecting the vacancy of the channel which might be occupied by a WFM signal. Error bars in Fig. 2 match confidence bands for proportions [9], confidence level 0.05. Analysis of the plots suggests that for $v \in \{1, 2\}$ rule (4) outperforms rule (3); for $v = 3$ the difference is subtle. Also, rules (3) and (4) exhibit better performance compared to the energy detector, especially at low SNRs. Rule (4) is recommended for use when both operation time and $\mathsf{P}(1|1)$ are equally important for the end user. If we are looking for keeping high values of $\mathsf{P}(1|1)$ while minimizing operation time, rule (2) comes into play.



(a) AFS FSK 130 Bd signal (b) Wide band FM (WFM) signal

Fig. 1. Magnitude spectra of signals treated as unknown ones

B. Procedure for Selection and Recognition of Given Signals

In sub-Sec. II-B decision rule (6) for selection and recognition of specified signals in the presence of unknown ones was described. Such a procedure lends itself well to constructing a signal spectrum sensing system for CRs. Indeed, spectrum sensing is performed as a two-step procedure. First, we are looking for familiar to the CR system signals and if we have serially rejected hypotheses for the presence of all known signals, we proceed to answering the question whether we deal with an unspecified signal or noise. That is, if the test for properties of noise of the observed signal have been rejected, we declare the signal to be unknown one and update the CR database. The Type I error rate for both of our hypothesis testing steps was selected in accordance with the Bonferroni procedure [10], [11]. It was equal $\alpha_{\text{f-w}}/2$. Here $\alpha_{\text{f-w}}/2$ is for the desired significance level of the sensing procedure. More details on the this spectrum sensing procedure are in [12].

Below we report results of simulations, which were done in MATLAB. In our experiment we used samples of 6 kHz signals. Learning and testing samples were composed of 100 realizations each. Every realization was represented by a vector of 128 time bins. As before, the processing is done in the frequency domain ($L = 64$). Fig. 3 plots normalized averaged magnitude spectra of the signals.

It is known that power spectrum bins are asymptotically independent, thus we supposed components of the input vectors to be uncorrelated. That is, the distances D^i, used in (6), take on the form

$$D^i = \sum_{j=1}^{L} \frac{(x_j - \mu^i_j)^2}{(\sigma^i_j)^2}, \quad i = \overline{1, M},$$

where $\vec{X} = [x_1, x_2, \ldots, x_L]^T$, $\vec{\mu^i} = [\mu^i_1, \mu^i_2, \ldots, \mu^i_L]^T$, $\mathbf{R}^i = \operatorname{diag}((\sigma^i_1)^2, (\sigma^i_2)^2, \ldots, (\sigma^i_L)^2)$. Among signals in Fig. 3, the first four (i.e. #1 through #4) were treated as known ones, while the rest (#5 through #8) we considered as unknown signals. Thus, in our particular case $M = 4$. The channel noise signal was included into the category of unknown signals and had the sequence number #5. Thresholds $\Delta^i, \ i = \overline{1, M}$ were found to match the significance level $\alpha = 0.05/2 = 0.025$. Results of recognition are summarized in Tab. I.

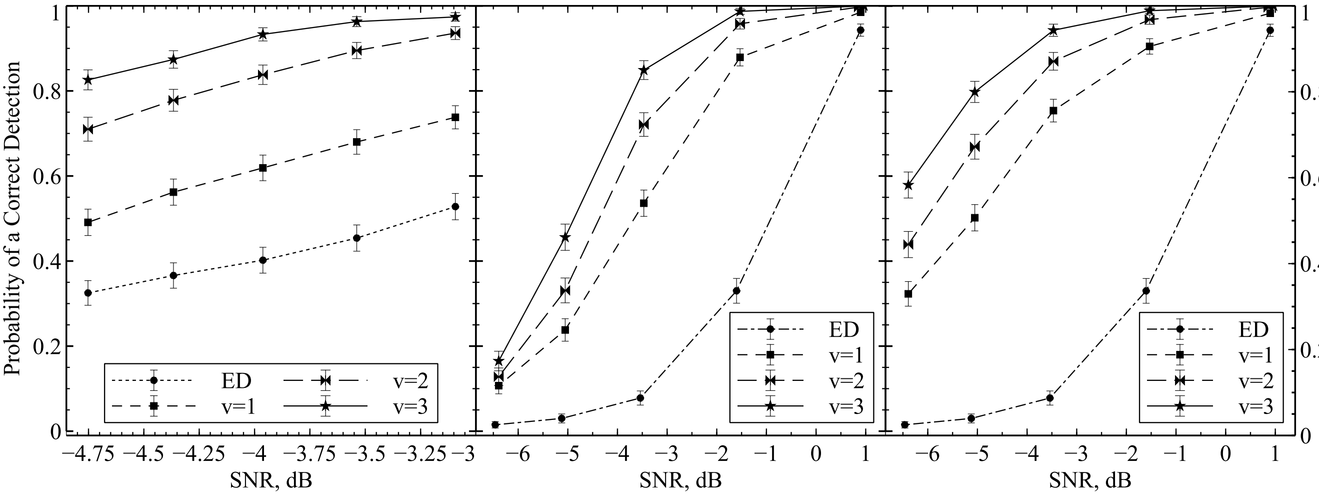


Fig. 2. Behavior of decision rules, from left to right: rule (3) / AFS FSK 130 Bd; rules (3) and (4) / WFM signal.

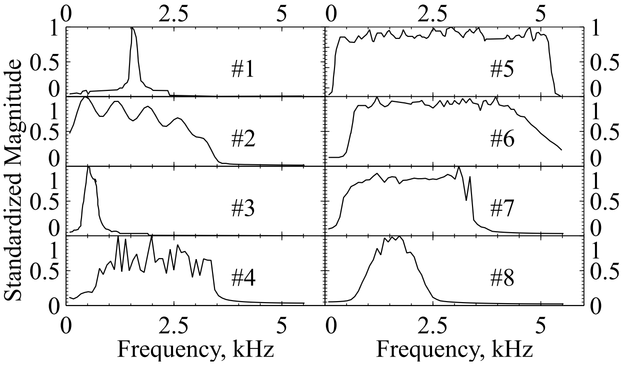


Fig. 3. Standardized averaged magnitude spectra of signals.

Analyzing Tab. I data we see that #7 was erroneously assigned to #4 because of the lack of learning samples corresponding to it. The rest of unknown signals have been referenced properly to the $(M+1)$-th class. From the perspective of the CR smooth operation the registered signal entanglement influences nothing as as we are looking for not occupying a used by primary user channel, which we do achieve.

IV. Conclusion

The ability to reference unknown signals to a special class of signals, suggests described in the paper two-stage decision making procedure. At the first stage the input signal is tested for being a known one, while at the second stage all the signals, labeled as unknown ones, are tested for exhibiting features of the channel noise. Despite being conservative, this procedure allows us to substantially reduce chances for occupying a previously engaged by the primary user channel, which is one of CRs' main objectives.

TABLE I
Results of Signal Selection and Recognition

$\mathsf{P}(i\|j)^{\mathrm{a}}$	Signal j							
	1	2	3	4	5	6	7	8
$\mathsf{P}(1\|j)$	.97	.00	.00	.00	.00	.00	.00	.00
$\mathsf{P}(2\|j)$	.00	.66	.00	.00	.00	.00	.00	.00
$\mathsf{P}(3\|j)$	.00	.34	.96	.00	.00	.00	.00	.00
$\mathsf{P}(4\|j)$	.00	.00	.00	.90	.00	.00	.65	.00
$\mathsf{P}(M+1\|j)$	.03	.00	.04	.10	1.0	1.0	.35	1.0

$^{\mathrm{a}}\mathsf{P}(i|j)$ is for probability of referencing signal j to class i.

References

[1] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," in *Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, 2004.*, vol. 1, no. Nov, 2004, pp. 772–776.

[2] A. M. Rembovsky, A. V. Ashikhmin, V. A. Kozmin, and S. M. Smolskiy, *Radio Monitoring*, ser. Signals and Communication Technology. Springer International Publishing, 2018.

[3] Ž. Tabaković, "A survey of cognitive radio systems," Jan 2008. [Online]. Available: https://www.researchgate.net/publication/228450166_A_Survey_of_Cognitive_Radio_Systems

[4] B. Wild and K. Ramchandran, "Detecting primary receivers for cognitive radio applications," in *First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005.*, 2005, pp. 124–130.

[5] T. Yücek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Communications Surveys & Tutorials*, vol. 11, no. 1, pp. 116–130, 2009.

[6] V. M. Bezruk and G. V. Pevtsov, *Theoretical Foundations of Signal Recognition Systems Design for Automated Radio Monitoring*. Kharkov: Collegium, 2007, *(in Russian)*.

[7] T. D. Wickens, *Elementary signal detection theory*. Oxford University Press, USA, 2002.

[8] G. Gallego, C. Cuevas, R. Mohedano, and N. García, "On the mahalanobis distance classification criterion for multidimensional normal distributions," *IEEE Transactions on Signal Processing*, vol. 61, no. 17, pp. 4387–4396, Sep. 2013.

[9] R. Stine and D. Foster, *Statistics for Business: Decision Making and Analysis*. Pearson Education, 2014.

[10] H. Abdi, "Bonferroni test," in *Encyclopedia of measurement and statistics*, N. Salkind, Ed. Thousand Oaks, Calif: SAGE Publications, 2006, vol. I, pp. 103–107.

[11] C. Helberg, "Multiple comparisons," in *Encyclopedia of measurement and statistics*, N. Salkind, Ed. Thousand Oaks, Calif: SAGE Publications, 2006, vol. I, pp. 644–648.

[12] V. Bezruk, S. Ivanenko, O. Fedorov, Z. Němec, and J. Pidanič, "Methods of signal detection and recognition to perform frequency resource sharing in cognitive radio networks," in *Future Intent-Based Networking*, M. Klymash, M. Beshley, and A. Luntovskyy, Eds. Cham: Springer International Publishing, 2022, pp. 392–409.