Signal Classification in Heterogeneous OFDM-based Cognitive Radio Systems

Wael Guibène
EURECOM-Campus SophiaTech
Mobile Communication Dpt.
Email: Wael.Guibene@eurecom.fr

Dirk Slock
EURECOM-Campus SophiaTech
Mobile Communication Dpt.
Email: Dirk.Slock@eurecom.fr

***Abstract*—In this paper, we propose to study the spectrum awareness also called classification of various signals enabling the OFDM-based cognitive radio systems (CRS). In order to do so, some key properties relevant to the detection of the OFDM-based third-Generation Partnership Project Long Term Evolution (3GPP LTE) and digital video broadcast for terrestrial TV (DVB-T) signals as well as programme-making and special events (PMSE) signals are derived and a robust classification scheme based on parallel standards discrimination is derived. Simulations results for the proposed technique show its effectiveness and robustness to additive white Gaussian noise channels as well as Rayleigh multipath fading plus shadowing channels.**

***Index Terms*—Signal classification, Spectrum Awareness, OFDM signals, LTE, DVB-T, PMSE.**

I. Introduction

Cognitive radio (CR) was presented by Mitola [1] as one the promising technologies enabling the dynamic spectrum access and sharing the spectral resources between different users. Another interesting definition was given by the IUT-R, describing the cognitive radio 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". In a cognitive radio system (CRS) two class of users try to cohabitate: licensed users, also called primary users (PUs) and the opportunistic users, also called secondary users (SUs). The SU tries to gain access to the licensed spectrum when the PU is not occupying his resources (spectrum/time). And this monitoring of PU presence/abscence is called spectrum sensing feature of the CR. In overlay spectrum sharing policies, this knowledge of the operational environment come from the spectrum sensing feature of the cognitive radio.

The other main functions of Cognitive Radios, apart from spectrum sensing are:

- Spectrum management: which captures the most satisfying spectrum opportunities in order to meet both PU and SU quality of service (QoS).
- Spectrum mobility: which involves the mechanisms and protocols allowing frequency hopes and dynamic spectrum use.
- Spectrum sharing: which aims at providing a fair spectrum sharing strategy in order to serve the maximum number of SUs.

The presented work fits in the context of spectrum sensing/spectrum sharing framework for CR networks and more precisely single node detection/ standard identification. Related to this work, many statistical approaches for the spectrum sensing part have been developed. One of the most performing sensing techniques is the cyclostationary features detection [2], [3]. The main advantage of the cyclostationarity detection is that it can distinguish between noise signal and PU transmitted data. Indeed, noise has no spectral correlation whereas the modulated signals are usually cyclostationary with non null spectral correlation due to the embedded redundancy in the transmitted signal. The reference sensing technique is the energy detector [2], as it is the easiest to implement and the less complex detection technique. On the other hand, some papers have been dedicated to the signal identification part [4]–[6]. In this paper, we present a robust classification technique based on parallel spectrum sensing techniques in order to combine the sensing / classification feature of the CR. In section II, we present the targeted scenario, where the network to be considered is a heterogeneous network with at least three types of coexisting signals (LTE, DVB-T and PMSE signals). In section III, we go through the details of the proposed classification scheme based on parallel and simultaneous spectrum sensing techniques. In section IV, we propose to evaluate the proposed scheme with two scenarios and finally section V concludes about the present work.

II. Targeted Scenarios

The goal of this paper is to derive a classification scheme for different systems with specific parameters and signal characteristics, operating in the TV White Spaces (TVWS). The transmitters considered in SACRA/SPECTRA are identified and characterized below:

1) A DVB-T Primary User (PU) which uses an OFDM modulation. As shown later, there are several DVB-T configurations, depending on
   a) the bandwidth (5 MHz, 6 MHz, 7 MHz, 8 MHz) of the channel being used,
   b) the modulation (QPSK/QAM/16-QAM/64-QAM) used by the subcarriers from the OFDM symbol,

c) the useful symbol and guard periods: system characteristics have been predefined by standards, and they are fixed known values for the useful T_U and guard T_G period (the latter is also called cyclic prefix period).

2) An LTE Secondary User (SU) which uses OFDM Modulation (in downlink DL) and SC-FDMA (in uplink UL) combined with BPSK/QAM/16-QAM/64-QAM. System characteristics with fixed symbol and guard periods (T_U and T_G) have been predefined by 3GPP standardization activities.
3) A PMSE PU which uses QPSK Modulation (400 KHz Bandwidth) or FM Modulation (200 KHz). Excepting the bandwidth, the system characteristics are not very well defined for PMSE. These devices will further be discussed in latter sections.

In Figure (1), terminal UE5 is connected to a base station operating through the licensed band (2.6GHz), eNB3, and may be authorized to use resources in another band (DD/TVWS) to communicate with a second base station, eNB1. This use case is based on the spectrum aggregation concept, introduced in LTE-Advanced standard. The terminal is thus operating in a heterogeneous network, with OFDM LTE-A, OFDM DVB-T and PMSE signals cohabitating in the network. From this coexistence came the need to classify each standard in order to enable the opportunistic use of the TVWS bands.

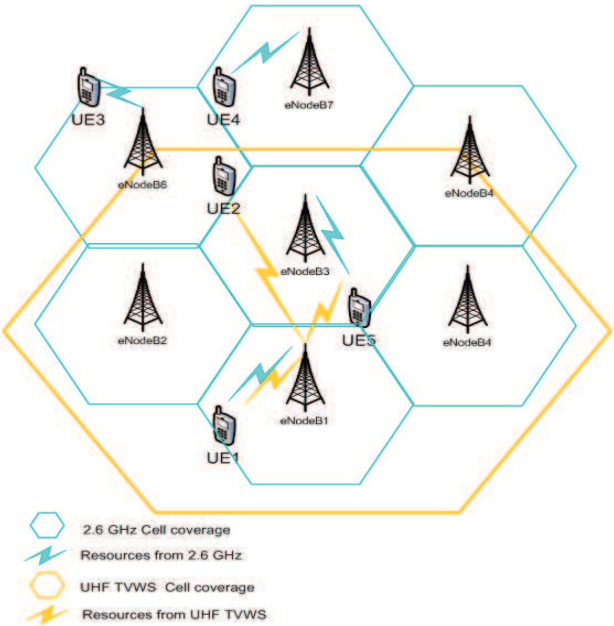

Fig. 1. Targeted wide-band cognitive radio network scenario

III. The Signal Classifier Scheme

A. Conventional Spectrum Sensing for CRS

In order to model the spectrum sensing problem, let's suppose that the detector receives signal $y_n = A_n s_n + e_n$, where A_n models the channel, s_n is the transmit signal sent from primary user and e_n is the additive noise. The goal of spectrum sensing is to decide between two conventional hypotheses modeling the spectrum occupancy H_0 and H_1 modeling respectively, the decision by the detector of PU signal absence and presence. In order to make such a decision, the detector implements a scalar test statistic Λ function of the input signal y_n. This test statistic is to be compared to a threshold level γ function of the SNR and the probability of false alarm P_{FA} and we thus obtain:

$$\begin{cases} \text{if } \Lambda = \mathfrak{F}(y_n) \geq \gamma & \text{decide } \mathcal{H}_1 \\ \text{if } \Lambda = \mathfrak{F}(y_n) < \gamma & \text{decide } \mathcal{H}_0 \end{cases} \quad (1)$$

In the proposed classification scheme, we proposed to mount as many parallel detectors as the number of standards we would like to discriminate. In this work for example, we would like to focus on two OFDM-based standards (LTE, DVB-T) and PMSE signals (for wireless microphones), therefore the classifier would have three parallel stages.

B. Multistandard Classification Technique for CRS

In this section, we briefly present each signal to be classified and the corresponding test statistic and threshold to be applied for the each detection stage. Since we are considering three standards, the proposed classifier has to implement three stages as presented and explained afterwards.

1) DVB-T signals detection: For the detection of DVB-T signals, a robust algorithm to be applied could be the autocorrelation based detector (AD). This technique is based on the fact that many communication signals contain redundancy, introduced for example to facilitate synchronization, by channel coding or to circumvent inter-symbol interference. This redundancy occurs as non-zero average autocorrelation at some time lag l. The autocorrelation function at some lag l can be estimated from:

$$\hat{r}_l(y) = \frac{1}{p-l} \sum_{n=0}^{p-l-1} y_{n+l}\, y_n^* \qquad l \geq 0 \quad (2)$$

where p is the length of the PU signal in samples. Any signal except for the white noise case will have values of the autocorrelation function different from zero at some lags larger than zero, although some might be exactly zero depending on the zero crossings. In [7], authors have proposed an autocorrelation-based detector for DVB-T OFDM signals. This detector is limited to the case when the PU is using DVB-T. To detect the existence/non existence of signal we use functions of the autocorrelation lags, where the autocorrelation is based on (2). Therefore, the autocorrelation-based decision statistic is given by [8]

$$\Lambda_{DVBT-AD}(y) = \sum_{l=1}^{L} w_l \frac{\text{Re}\{\hat{r}_l\}}{\hat{r}_0} \quad (3)$$

where the number of lags, L, is selected to be an odd number. The weighting coefficients w_l could be computed to achieve the optimal performance, and is given by:

$$w_l = \frac{L+1+|l|}{L+1} \quad (4)$$

2) LTE signals detection: As far as LTE is concerned, we apply a second order cyclostationary features detector (CFD) in order to fully cover LTE standards classification. The algorithm we are adopting is fully described in [9]. To sum-up, the algorithm is based on the fact that LTE-OFDM signals exhibit reference signals-introduced second-order cyclostationarity with the cyclic autocorrelation function (CAF), $R_y^\alpha(\tau) \neq 0$ at cyclic frequency $\alpha = 0$ and delay $\tau = D_F$ (D_F is the frame duration) for all transmission modes. This property exhibited by FDD downlink LTE-OFDM transmissions can thus be used to detect presence of LTE signals regardless of the mode. The CAF of the received signal, y_n, is estimated from N_s samples at the delay τ and the CF α and we form the following vector: $\widehat{R}_y^\alpha = [\mathrm{Re}(R_y^\alpha(\tau))\mathrm{Im}(R_y^\alpha(\tau))]$ in order to compute the test statistic given by:

$$\Lambda_{LTE-CFD} = N_s \widehat{R}_y^\alpha \widehat{\Sigma}^{-1} (\widehat{R}_y^\alpha)^t \quad (5)$$

where $\widehat{\Sigma}$ is the estimate of the $\widehat{R}_y^\alpha$ covariance matrix.
The test statistic $\Lambda_{LTE-CFD}$ has now to be compared to some threshold value λ to make the decision. As previously stated, this threshold is function of the probability of false alarm P_{FA}. In our case, and given the test statistic, a possible definition of P_{FA} could be: the probability of deciding that the tested frequency α is a CF at delay τ when this is actually not. frequency is a CF at delay, or : $P_{FA} = \Pr(\Lambda_{LTE-CFD} \geq \lambda|\mathrm{H}_0)$. keeping in mind that $\Lambda_{LTE-CFD}$ is following a chi-squared distribution [10], the threshold λ is obtained from the tables of the chi-squared distribution for a given value of P_{FA} probability.

3) PMSE signals detection: For the PMSE signal, we opt for a wireless-microphones oriented detector: the Teager-Kaiser energy detector for narrowband wireless microphone as presented in [11]. The PMSE signal as transmitted from the PMSE equipment can be modeled by:

$$x(t) = A\cos(2\pi f_0 t + \frac{\kappa_f}{s_m}\int_\tau s(\tau)d\tau) \quad (6)$$

where where f_0 is the carrier frequency, κ_f the frequency deviation of the FM modulation, and $s(t)$ the modulating signal having an amplitude of s_m. The signal $x(t)$ has a power $\sigma_x^2 = A^2/2$. And the received signal over an AWGN is :

$$y(t) = x(t) + n(t) \quad (7)$$

In order to derive the test statistic of this detector, The Teager-Kaiser energy operator Ψ is used to extract directly the energy from the instantaneous signal and is expressed by:

$$\Psi[y(k)] = \Psi[x(k)] + \Psi[n(k)] + 2\Psi[x(k), n(k)] \quad (8)$$

and since the noise and the signal are uncorrelated, $\Psi[x(k), n(k)] = 0$. and the test statistic is the average value of Teager-Kaiser energy operator applied to $y(k)$, expressed as:

$$\begin{aligned} \Lambda_{PMSE-TKED} &= E\langle\Psi[y(k)]\rangle & (9) \\ &= E\langle\Psi[x(k)]\rangle + \sigma_n^2 & (10) \end{aligned}$$

For this detector, we will use a Monte-Carlo simulation to derive the desired threshold function of the P_{FA}.

4) Combining rule for Classification: So far, the choice made for each detectors was based on the criterion that each sensing technique should be suitable for only one standard. That is why the choice for DVB-T was the autocorrelation detector (DVBT-AD) that highlights the DVB-T characteristics among the other standards; and for LTE we opted for the second order cyclostationary feature detector (LTE-CFD); and finally for PMSE signal we used the Teager-Kaiser energy operator (PMSE-TKED) that is convenient for narrowband signals. In order to combine the outputs of these standard-dedicated detectors, we will fuse the data from different stages of OFDM-based techniques as in Equation (11).

In Equation (11), for the two first decisions, we won't focus on TKED output, as if it is an LTE or DVB-T signal it has an output energy greater than the threshold, so its output is $\mathcal{H})_1$. We will focus rather on the outputs of the CFD and the AD in order to discriminate between LTE and DVB-T respectively. We will focus on TKED only when the CFD and AD give both null hypothesis testing results $\mathcal{H}_0$.

IV. Simulations and Results

A. Simulation Settings

We define two scenarios to evaluate the proposed solution:

- **Scenario 1:** In this scenario, we use DVB-T and LTE OFDM signals plus a QPSK wireless microphone as PMSE signal over an AWGN channel. It is assumed that the detection performance in AWGN will provide a good impression of the performance, but it is necessary to extend the simulations to include signal distortion due to multipath and shadow fading.
- **Scenario 2:** In this case, we use the same signals as Scenario 1, but to make the simulations more realistic, the signal is subjected to Rayleigh multipath fading and shadowing following a log normal distribution in addition to the AWGN. The maximum Doppler shift of the channel is 100Hz and the standard deviation for the log normal shadowing is 10dB.

The simulation parameters used in this paper for the DVB-T signals are are given in [12], [13], while LTE signals are of bandwidth 10 MHz and using short cyclic prefix (CP). For more details on LTE parameters used in this paper see ref [14], [15] and [16] for LTE specifications and simulations. And as far as PMSE signals are concerned a QPSK narrowband signal was considered for the simulation of wireless microphones.

B. Simulation Results

Figures (2) and (3), report the results of the two simulated scenarios. A general remark that could be made is that the

$$\begin{cases} \text{if } \frac{\Lambda_{DVBT-AD}}{\gamma_{AD}} \geq 1 \text{ and } \frac{\Lambda_{LTE-CFD}}{\gamma_{CFD}} < 1 & \text{decide } \mathcal{H}_{DVB-T} \\ \text{if } \frac{\Lambda_{LTE-CFD}}{\gamma_{CFD}} \geq 1 \text{ and } \frac{\Lambda_{DVBT-AD}}{\gamma_{AD}} < 1 & \text{decide } \mathcal{H}_{LTE} \\ \text{if } \frac{\Lambda_{PMSE-TKED}}{\gamma_{TKED}} \geq 1 \text{ and } \frac{\Lambda_{DVBT-AD}}{\gamma_{AD}} < 1 \text{ and } \frac{\Lambda_{LTE-CFD}}{\gamma_{CFD}} < 1 & \text{decide } \mathcal{H}_{PMSE} \end{cases} \tag{11}$$

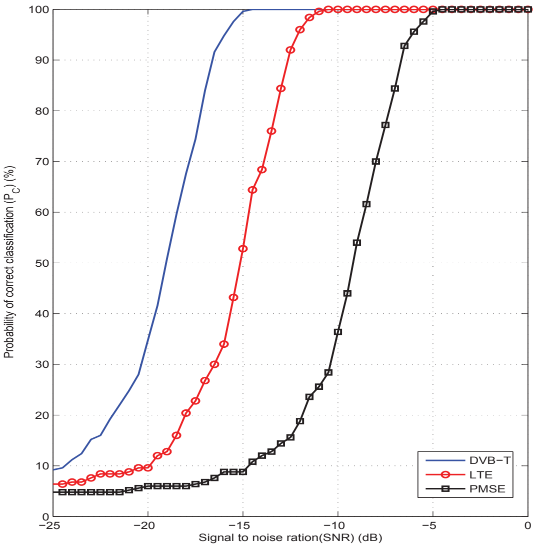

Fig. 2. Probability of correct classification (P_C) Vs. Signal to Noise Ratio (SNR) for a Probability of False Alarm P_{FA}= 0.05 and classification period of 25 ms: Scenario 1

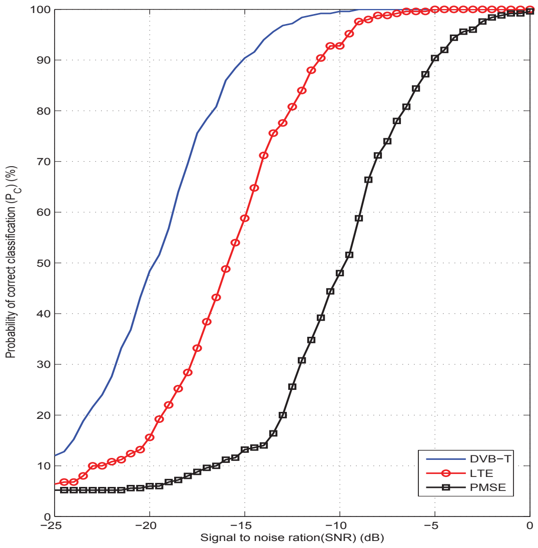

Fig. 3. Probability of correct classification (P_C) Vs. Signal to Noise Ratio (SNR) for a Probability of False Alarm P_{FA}= 0.05 and classification period of 25 ms: Scenario 2

DVB-T classification outperforms LTE and PMSE. That is fully comprehensible as for DVB-T the detection is made using the autocorrelation function of the whole signal, but for LTE we only made it for the RS (reference signals) which makes the correlation length lower than the DVB-T one; and this gets worst for PMSE as the signal itself is a narrowband one ($Bandwidth \leq 400KHz$). In Figure (2), the classification is done over an AWGN channel for 25 ms acquisition which is meant to give a first overview of the classifier performance and in Figure (3), for the same period the classification scheme is tested under a more realistic channel model, a Rayleigh multipath fading and shadowing following a log normal distribution in addition to the AWGN. The maximum Doppler shift of the channel is 100Hz and the standard deviation for the log normal shadowing is 10dB.

V. Conclusion

In this paper we presented a novel robust classification scheme. The use-case considered in this paper is the SACRA/SPECTRA projects case which, without any loss of generalities can be extended to any other cognitive network scenario. The robustness of the proposed classifier resides in the choice of the sensing algorithm for each standard. Here the AD was chosen for DVB-T because it was assumed to be the best detector exploiting the OFDM DVB-T properties and so is the choice for CFD for OFDM LTE standard, but since the PMSE signals are quite hard to model in terms of statistics, we opted for the exploitation of the narrowband property of those signals.

Acknowledgment

The research work leading to these results has received funding from the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement SACRA Project number 249060, WHERE2 Project ICT-248894 and FP7 CELTIC SPECTRA Project.

References

[1] J Mitola, *Cognitive radio: An integrated agent architecture for software defined radio*, Doctor of Technology, Royal Inst. Technol.(KTH), 2000.
[2] T.Yucek, H.Arslan, *A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications*, IEEE Communications Surveys & Tutorials 2009, pages 116-130.

[3] S. Xu, Z. Zhao, J. Shang, *Spectrum Sensing Based on Cyclostationarity*, Workshop on: Power Electronics and Intelligent Transportation System, 2008. PEITS '08, Aug. 2008.

[4] W. Guibene, D. Slock, *Signal Separation and Classification Algorithm for Cognitive Radio Networks*, ISWCS-12, The 9th International Symposium on Wireless Communication Systems, August 28-31, 2012, Paris, France

[5] D. Panaitopol, A. Bagayoko, C. Mouton, P. Delahaye and G. Abril, *Primary User Identification when Secondary User is Transmitting without using Quiet Period*, 12th International Symposium on Communications and Information Technologies (ISCIT 2012), Gold Coast, Australia, October 2012

[6] SACRA FP7 project, Deliverable 2.2, "Spectrum and Energy Efficiency through multi-band Cognitive Radio," version 1.1, Jan. 2012.

[7] S. Chaudhari, V. Koivunen, H. V. Poor, Autocorrelation-Based Decentralized Sequential Detection of OFDM Signals in Cognitive Radios," *IEEE Trans. Sig. Proc.*, vol. 57, no. 7, pp. 2690–2700, July 2009.

[8] M. Naraghi-Pour and T. Ikuma. *Autocorrelation-based spectrum sensing for cognitive radios*. IEEE Transactions on Vehicular Technology, 59(2), Feb. 2010

[9] A. Al-Habashna, A. O. Dobre, R. Venkatesan, C. D. Popescu, "Second-Order Cyclostationarity of Mobile WiMAX and LTE OFDM Signals and Application to Spectrum Awareness in Cognitive Radio Systems," *IEEE J. Sel. Topics Signal Process.*, vol. 6, no. 1, pp. 26–42, Feb. 2012.

[10] A. V. Dandawate and G. B. Giannakis, *Statistical tests for presence of cyclostationarity*, IEEE Trans. Signal Process., vol. 42, no. 9, pp. 2355–2369, Sep. 1994

[11] M. Gautier, V. Berg, D. Noguet, *Wideband frequency domain detection using Teager-Kaiser energy operator*, IEEE 5th International Conference on Cognitive Radio Oriented Wireless Networks and Communications (Crowncom'12), Stockholm, Sweeden 2012

[12] D. Danev, "On signal detection techniques for the DVB-T standard", *Proc. ISCCSP*, March 2010.

[13] Final draft ETSI EN 300 744 V1.5.1 (2004-06), "Digital Video Broadcasting (DVB): Framing structure, channel coding and modulation for digital terrestrial television", June 2004.

[14] 3GPP TR 36.913 V8.0.1 (Release 8), Requirements for further advancements for E-UTRA, March 2009.

[15] LTE Simulator, http://www.nt.tuwien.ac.at/ltesimulator/

[16] C. Mehlfuhrer, M. Wrulich, J. C. Ikuno, D. Bosanska, M. Rupp, Simulating the Long Term Evolution physical layer, *Proc. EUSIPCO*, Aug. 2009