Signal Separation and Classification Algorithm for Cognitive Radio Networks

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***Abstract*—In the context of spectrum sharing, many approaches were developed and many algorithms were proposed in order to model and regulate the use of spectral resources. Despite the proposed solutions and spectrum access policies, there is still a big issue in cognitive radio networks with users who may intend (or not) to violate these communication rules and force their radios to access the spectrum bands when some other users are already communicating. These users become hostile terminals in the network and the fusion center has to eliminate their interfering signals. In this context we[1] propose a mixed signals separation and classification algorithm that helps eliminating hostile devices. The first step consists in locating the frequency band over which the hostile terminal is communicating and then, by some mixed signals separation technique, isolate and then eliminate its interfering signal by analyzing the obtained signals from the mixture. For the simulations, we introduced some metric for the probability of detecting and classifying the hostile terminal as such.**

***Index Terms*—mixed signal separation, cognitive radio, signals classification, spectrum sharing**

I. Introduction

During the last decades, we have witnessed a shortage and high misuse of radio resources. Facing this lack of resources, telecommunication regulators, and standardization organisms recommended sharing this valuable resource between the different actors in the wireless environment. The federal communications commission (FCC), for instance, defined a new policy of priorities in the wireless systems, giving some privileges to some users, called primary users (PU) and less to others, called secondary users (SU), who will use the spectrum in an opportunistic way with minimum interference to PU systems.

Cognitive radio (CR) as introduced by Mitola, is one of those possible devices that could be deployed as SU equipments and systems in wireless networks. As originally defined, a CR is a self aware and "intelligent" device that can adapt itself to the Wireless environment changes. Such a device is able to detect the changes in wireless network to which it is connected and adapt its radio parameters to the new opportunities that are detected. This constant track of the environment change is called the "spectrum sensing" function of a CR device. Thus, spectrum sensing in CR aims in finding the holes in the PU transmission which are the best opportunities to be used by the SU. Considerable efforts and lots of algorithms were made within this sensing framework [1].

Still, a master piece of cognitive radio is missing and ignored by many many people when talking about cognitive radio and generally dynamic spectrum access. In a perfect scenario, cognitive terminals, would be guaranteed to access the spectral resources and share them in a "fair" strategy. Unfortunately, this remains as a perfect and an optimistic scenario i.e, some cognitive terminals may ignore and disobey the sharing rules leading to the emergence of new group in the frequency band referred to as "hostile terminals". These CR would use the frequency resources at their own will and thus create interference to the other cognitive radios. In this sense, locating (in frequency) and eliminating the signals of those hostile terminals is also considered as a major task in cognitive radio networks (CRN).

In this paper, we present our algorithm that operates in three steps in order to locate (in frequency) and eliminate the harmful cognitive radio signals by separating them from the mixed signal and recovering back the desired unharmful signal. By applying a frequency edge detection, we will be able to target the exact band in which the interfering terminal is, eliminate it and recover back the signal from the terminal(s) which is(are) allowed to transmit. In [6], the authors proposed a wavelet edge detection technique in order to locate the hostile terminals signals. We propose using a more robust and a less computational cost approach, which is the algebraic toolbox for spectrum edge location. The second step of the algorithm, consists in deploying a blind source separation technique in order to separate the mixed signal and infer which signal(s) is the harmful one.

The rest of the paper is organized as following: in section II we presented the system and the targeted scenario. In section III, we introduce our proposed solution to the mixed signal separation and classification problem. Then, in section IV, some simulation results are presented and discussed. Finally, in section V, we conclude about the presented work.

II. System Description and Targeted Scenario

The adopted solution to the problem of hostile device presence consists in tracking and locating the band which is affected by its communication, separating the signals over this

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frequency band, analyzing the separated signals and finally eliminate the interfering signal.

The two critical phases in this process is how to locate the interfering signal? and how to separate it from the other signals?

In the general system and along with the SACRA (spectrum and energy efficiency through multi-band cognitive radio) European project [8], we propose the following scenario:

- The primary system is an LTE based system operating in 2.6GHz.
- The secondary network is targeting to use TV white space (TVWS) in TV bands.

So, the cognition will be done as usual in the TVWS, given that if a SU is already transmitting, it would be transmitting in a TVWS free sub-band with LTE specifications and that a hostile terminal would come interfere in the same band with DVB-T based signal.

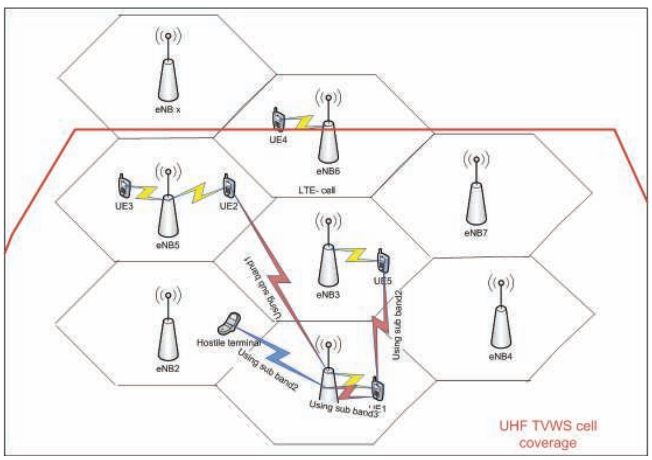

Fig. 1. Targeted wide-band cognitive radio network scenario

As shown in figure 1, connection is established on the request of the UE5 for various reasons such as originated audio call. The eNB3 is establishing a connection with the primary cell in the licensed band which is the main carrier for the UE. Due to QoS requirements of the application for the UE5, eNB3 is requesting to find additional resources for this UE. eNodeBs are coordinated to select correct bands for use by UE5. The eNB1 is configuring carrier component in the opportunistic band to enhance the throughput for the UE5. eNB1 and eNB3 are coordinating the scheduling of data through two carrier components allowing simultaneously communication in the two bands for UE5. In this scenario, we clearly see that the hostile terminal, starts to use the same sub-band allocated by the network to UE5-eNB1 communication, this causes harmful interference to the QoS of the communication established between UE5 and eNB1.

III. Proposed Algorithm for Signal Separation in Cognitive Radio Networks

The proposed algorithm for signals separation in CRN contains three steps: a frequency edge location, the separation process and finally a classification step. The frequency edge location will determine exactly where the interfering signal location is, and the mixed signal separation will allow us to eliminate this interference.

Let M be the number of terminals in the proposed CRN architecture and N be the number of source signals.
The received wideband signal can be written as following:

$$x(t) = A \ . \ s(t) + n(t) \tag{1}$$

where $x(t)$ is a M-dimensional vector of the observed signals. $s(t)$ is a N-dimension vector corresponding to the source signals transmitted by the cognitive radios. The matrix A is $M \times N$, and denotes the mixing matrix. And $n(t)$ is the additive white noise vector having the same size as $x(t)$

A. Frequency Edge Location

In [3]–[5], Guibene *et al*, developed a spectrum sensing technique based on frequency edge location and exploiting spectrum discontinuities detection. Inspired from the already developed framework, we derive our edge location algorithm.

First we do suppose that the frequency range available in the wireless network is B Hz; so B could be expressed as $B = [f_0, f_K]$. Saying that this wireless network is cognitive, means that it supports heterogeneous wireless devices that may adopt different wireless technologies for transmissions over different bands in the frequency range. A CR at a particular place and time needs to sense the wireless environment in order to identify spectrum holes for opportunistic use. Suppose that the radio signal received by the CR occupies N spectrum bands, whose frequency locations and PSD levels are to be detected and identified. These spectrum bands lie within $[f_1, f_K]$ consecutively, with their frequency boundaries located at $f_1 < f_2 < ... < f_K$. The n-th band is thus defined by: $B_n : \{f \in B_n : f_{n-1} < f < f_n, \ n = 2, 3, ..., K\}$. The following basic assumptions are adopted:

1) The frequency boundaries f_1 and $f_K = f_1 + B$ are known to the CR. Even though the actual received signal may occupy a larger band, this CR regards $[f_1, f_K]$ as the wide band of interest and seeks white spaces only within this spectrum range.
2) The number of bands N and the locations $f_2, ..., f_{K-1}$ are unknown to the CR. They remain unchanged within a time burst, but may vary from burst to burst in the presence of slow fading.
3) The PSD within each band B_n is smooth and almost flat, but exhibits discontinuities from its neighboring bands B_{n-1} and B_{n+1}. As such, irregularities in PSD appear at and only at the edges of the K bands.
4) The corrupting noise is additive white and zero mean.

The input signal is the amplitude spectrum of the received noisy signal. We assume that its mathematical representation is a piecewise regular signal:

$$Y(f) = \sum_{i=1}^{K} \chi_i[f_{i-1}, f_i](f) p_i(f - f_{i-1}) + n(f) \tag{2}$$

where: $\chi_i[f_{i-1}, f_i]$: the characteristic function of the interval $[f_{i-1}, f_i]$, $(p_i)_{i\in[1,K]}$: an N^{th} order polynomials series, $(f_i)_{i\in[1,K]}$: the discontinuity points resulting from multiplying each $p_i$by a χ_i and $n(f)$:the additive corrupting noise.
Now, let $X(f)$ the clean version of the received signal given by:

$$X(f) = \Sigma_{i=1}^{K}\chi_i[f_{i-1}, f_i](f)p_i(f - f_{i-1}) \quad (3)$$

And let b, the frequency band, given such as in each interval $I_b = [f_{i-1}, f_i] = [\nu, \nu + b]$, $\nu \geq 0$ maximally one change point occurs in the interval I_b.
Now denoting $X_\nu(f) = X(f+\nu)$,$f \in [0, b]$ for the restriction of the signal in the interval I_b and redefine the change point which characterizes the distribution discontinuity relatively to I_b say f_ν given by:

$$y_n = \begin{cases} f_\nu = 0 & \text{if } X_\nu \text{ is continuous} \\ 0 < f_\nu \leq b & \text{otherwise} \end{cases} \quad (4)$$

Now, in order to emphasis the spectrum discontinuity behavior, we decide to use the N^{th} derivative of $X_\nu(f)$, which in the sense of Distributions Theory is given by:

$$\frac{d^N}{df^N}X_\nu(f) = [X_\nu(f)]^{(N)} + \sum_{k=1}^{N}\mu_{N-k}\delta(f - f_\nu)^{(k-1)} \quad (5)$$

where: μ_k is the jump of the k^{th} order derivative at the unique assumed change point:f_ν

$$\mu_k = X_\nu^{(k)}(f_\nu^+) - X_\nu^{(k)}(f_\nu^-)$$

with : $\begin{cases} \mu_k = 0\rfloor_{k=1..N} & \text{if there is no change point.} \\ \mu_k \neq 0\rfloor_{k=1..N} & \text{if the change point is in } \mathrm{I_b}. \end{cases}$

$[X_\nu(f)]^{(N)}$ is the regular derivative part of the N^{th} derivative of the signal.
The spectrum sensing problem is now casted as a change point f_ν detection problem. In a matter of reducing the complexity of the frequency direct resolution, the equations are transposed to the operational domain, using the Laplace transform:

$$\begin{aligned} L(X_\nu(f)^{(N)}) = & \quad s^N\widehat{X_\nu}(s) - \textstyle\sum_{m=0}^{N-1} s^{N-m-1}\frac{d^m}{df^m}X_\nu(f)\rfloor_{f=0} \\ = & \quad e^{-sf_\nu}(\mu_{N-1} + s\mu_{N-2} + .. + s^{N-1}\mu_0) \end{aligned} \quad (6)$$

Given the fact that the initial conditions and the jumps of the derivatives of $X_\nu(f)$ are unknown parameters to the problem, in a first time we are going to annihilate the jump values μ_0,μ_1,...,μ_{N-1} then the initial conditions as fully detailed in [3]. After some calculations steps detailed, we finally obtain:

$$\sum_{k=0}^{N-1}\binom{N}{k}.f_\nu^{N-k}.(s^N\widehat{X_\nu}(s))^{(N+k)} = 0 \quad (7)$$

In the actual context, the noisy observation of the amplitude spectrum $Y(f)$ is taken instead of $X_\nu(f)$. As taking derivative in the operational domain is equivalent to high-pass filtering in frequency domain, which may help amplifying the noise effect. It is suggested to divide the whole equation 11 by s^l which in the frequency domain will be equivalent to an integration if $l > 2N$, we thus obtain:

$$\sum_{k=0}^{N-1}\binom{N}{k}.f_\nu^{N-k}.\frac{(s^N\widehat{X_\nu}(s))^{(N+k)}}{s^l} = 0 \quad (8)$$

Since there is no unknown variables anymore, the equations are now transformed back to the frequency domain, we obtain the polynomial to be solved on each sensed sub-band:

$$\sum_{k=0}^{N-1}\binom{N}{k}.f_\nu^{N-k}.L^{-1}[\frac{(s^N\widehat{X_\nu}(s))^{(N+k)}}{s^l}] = 0 \quad (9)$$

And denoting:

$$\varphi_{k+1} = L^{-1}[\frac{(s^N\widehat{X_\nu}(s))^{(N+k)}}{s^l}] = \int_0^{+\infty} h_{k+1}(f).X(\nu-f).df \quad (10)$$

where: $h_{k+1}(f) = \begin{cases} \frac{(f^l(b-f)^{N+k})^{(k)}}{(l-1)!} & 0 < f < b \\ 0 & otherwise \end{cases}$

In [2], it was shown that edge detection and estimation is analyzed based on forming multiscale point-wise products of smoothed gradient estimators. This approach is intended to enhance multiscale peaks due to edges, while suppressing noise. Adopting this technique to our spectrum sensing problem and restricting to dyadic scales, we construct the multiscale product of $N+1$ filters (corresponding to Continuous Wavelet Transform in [2]), given by:

$$Df = \| \prod_{k=0}^{N}\varphi_{k+1}(f_\nu)\| \quad (11)$$

B. Mixed Signal Separation

Now, in order to proceed with the blind source separation (BSS) like problem we ended with, and in order to adopt an independent component analysis (ICA) algorithm we have first to filter the wideband signal in a band of interest, modulate it to baseband, decorrelate and center the data, proceed with the FastICA and finally demodulate back the signal to its original frequency band.

1) Filtering:
In order to be able to separate the source signals from the mixture present in each subband, we need to analyse each subband separately. Thanks to the frequency edge location algorithm, we can sub-divide the wideband signal and thus obtain the frequency borders. By choosing two consecutive frequencies from the frequency set $\{f_n\}$, we can construct a filter h_{B_n} where $B_n = f_n - f_{n-1}$ is frequency support and $f_{nm} = (f_n - f_{n-1})/2$ is the center frequency.
Then in order to filter the signals between f_{n-1} and f_n, we get x_{in}: observed signal on each CR given by:

$$x_{in} = x_i * h_{B_n}, \quad i = 1, 2, .., M \quad (12)$$

where * denotes the convolution operation.
2) Signal Modulation:
As we intend to use some Blind Signal Separation

(BSS) processing, and as it is generally done in BSS, we modulate high frequency signals back to base band frequency. Thus we get:

$$x_{inL} = x_{in} * h_{Modn}, \quad i = 1, 2, .., M \tag{13}$$

where, x_{inL} is the modulated signal on each terminal and h_{Modn} represents the modulation carrier according to the estimated frequency edge. From this modulation process, we finally get a baseband signals matrix

$$X_{nL} = [x_{1nL}^T \;\; x_{2nL}^T ... \;\; x_{mnL}^T ... \;\; x_{MnL}^T]^T \tag{14}$$

3) Signals decorrelation and centering:
In order to proceed with BSS and ICA analysis of mixute, we have to make sure that the vector X_{nL} is uncorrelated and zero mean. Thus we proceed as following:
Centering Phase:

$$\widetilde{X}_{nL} = X_{nL} - E[X_{nL}] \tag{15}$$

now that the matrix $\widetilde{X}_{nL}$ is a zero-mean matrix, we can proceed to make it a non correlated matrix as classically done in BSS and ICA preprocessing. We also chose to ensure at the output of this process a unity variance for the uncorrelated matrix components.
Whitening Phase:

$$\widehat{X}_{nL} = E \; . \; D^{\frac{-1}{2}} \; . \; E^T \; . \; \widetilde{X}_{nL} \tag{16}$$

where E is the orthogonal matrix of eigenvectors of $E\{\widetilde{X}_{nL} \; . \; \widetilde{X}_{nL}^T\}$. $D = diag(d_1, ..., d_M)$ is the diagonal matrix containing the eigenvalues of $E\{\widetilde{X}_{nL} \; . \; \widetilde{X}_{nL}^T\}$.

4) Separation Technique:
Now that the matrix containing mixture signals is well conditioned, we can proceed to the signal separation step. In FastICA, which is one of the most used techniques for signals separation, the source signals in baseband, $\widehat{S}$, can be derived from the modulated, whitened, centered signal using a separation matrix, say W, as described by the following equation:

$$\widehat{S} = W^T \; . \; \widehat{X}_{nL} \tag{17}$$

In order to briefly describe the separation process, we initially choose an M-dimential weight vector, say w_{init}. Afterwards, the vectors has to be computed and updated in order to converge to W. The first component is computed at the first iteration by:

$$\begin{aligned} w_1^+ &= E\{\widehat{X}_{nL} \; . \; g(w_{init}^T \; . \; \widehat{X}_{nL})\} \\ &- E\{g'(w_{init}^T \; . \; \widehat{X}_{nL})\} \; . \; w_{init} \end{aligned} \tag{18}$$

then we normalize w_1 as following:

$$w_1 = \frac{w_1^+}{\|w_1^+\|} \tag{19}$$

where $g(\; . \;)$ is a non quadratic function that usually is chosen among: gaussian, hyperbolic tangent or a cubic function.

If w_1 does not converge, we proceed with equation (19) until $|w_1^T \; . \; w_{init}|$ gets as close as possile to 1.
Now, that w_1 converged,we get by successive iteration the $N-1$ (N and M are not necessarely equal) missing vectors of separation matrix. The k^{th} is computed at the k^{th} iteration by:

$$\begin{aligned} w_k^+ &= E\{\widehat{X}_{nL} \; . \; g(w_{k-1}^T \; . \; \widehat{X}_{nL})\} \\ &- E\{g'(w_{k-1}^T \; . \; \widehat{X}_{nL})\} \; . \; w_{k-1} \end{aligned} \tag{20}$$

then we normalize w_1 as following:

$$w_k = \frac{w_k^+}{\|w_k^+\|} \tag{21}$$

Therefore, after all these computations, we obtain the matrix $W = [w_1^T \;, \; w_2^T \; .... \;, w_N^T]$.
Now, having an estimate of the matrix W, we can compute the source signals and recontract S from the observed mixture from 17:

$$\widehat{S} = W^T \; . \; \widehat{X}_{nL} \tag{22}$$

where $\widehat{S} = [\widetilde{s}_{1nL}^T \;\; \widetilde{s}_{2nL}^T ... \;\; \widetilde{s}_{inL}^T ... \;\; \widetilde{s}_{NnL}^T]^T$, is the separated signals matrix. Given this notation, $\widetilde{s}_{inL}^T$ denotes the separated baseband signal vector.

5) Demodulation:
As a final step, we modulate $\widehat{S}$ back to its original subbands via the demodulation filter h_{demodn} constructed from the knowledge of h_{Modn}. and thus we get:

$$\widetilde{s}_{in} = \widetilde{s}_{inL} * h_{demodn}, \quad i = 1, 2, .., N \tag{23}$$

where $\widetilde{s}_{in}$ denotes the recovered signal vector on the frequency support delimited by f_{n-1} and f_n. And finally denoting, $\widetilde{S} = [\widetilde{s}_{1n}^T \;\; \widetilde{s}_{2n}^T ... \;\; \widetilde{s}_{in}^T ... \;\; \widetilde{s}_{Nn}^T]^T$, we do obtain the recovered signals matrix on each subband $[f_{n-1} \;, \; f_n]$.

Having this process done over one subband the analysis can be performed now on the entire subbands delimited by the set of frequencies $\{f_n\}$, until the whole wideband spectrum is fully analyzed.

C. Signals Classifications

In the targeted scenario, the cognition will be done as usual in the TVWS, given that if a SU is already transmitting, it would be transmitting in a TVWS free sub-band with LTE specifications and that a hostile terminal would come interfere in the same band with DVB-T based signal.

Now, we would need a metric on which we can rely to evaluate the separation algorithm. We suggest defining a new metric, which can summarize the performance of the output of the proposed technique. The metric has to consider the fact that we correctly separated and analyzed the separated signals. We propose than introducing the probability of right signals classification. This metric corresponds to the fact that the hostile terminal is correctly identified as a DVB-T signal on a the given sub-band of interest.

In order to achieve this, we will add a final classification step to our algorithm. In this step, in order to perform the classification of each separated signal, we deploy a cyclostationary feature detector-like algorithm but with a threshold and a test statistic adapted to the targeted standard to be classified. It is shown in literature that for a given signal, say $x(n)$, optimum feature classification is performed by correlating the cyclic periodogram with the ideal spectral correlation function of the targeted standard:

$$z = max_m \sum_{k=0}^{K} \widehat{S}_x^{\alpha}(k) W(m-k) \quad (24)$$

where $\widehat{S}_x^{\alpha}$ denotes the cyclic periodogram and is the rectangular window function. And as shown in [7] , the test statistic is given by:

$$\lambda = \frac{z}{z_0} \quad (25)$$

where z_0 is the computed value of the decision function for targeted standard to be classified. We define afterwards, the probability of correct classification which is the probability of classifying x as DVB-T, LTE:

$$P = p(z = z_0 | x) \quad (26)$$

IV. Simulations and Results

In order to evaluate the overall system performance, let's consider a simulation framework with the following signal properties:

Bandwidth	8MHz
Mode	2K
Guard interval	1/4
Frequency-flat	Single path
Sensing time	1.25ms
Location variability	10dB

TABLE I
SIMULATED SIGNALS PARAMETERS

The probability of correct classification as function of SNR applied on both separated signals for SNR values from -30 to 15 dB, and a fixed false alarm rate of 1% and a classification time of 1.25 ms and 250 ms is shown in Figure 2

In the figure 2, the SNR values correspond actually to the value of the mixture SNR,ie the received signal at the level of the fusion center. The fact that the performances decrease in low SNR region, comes from the contributions of noise to the separation process and its influence on the overall SINR of the separated signals. SACRA recommendations are shown to be achieved for classification period of 250 ms.

V. Conclusion

In this paper, we presented a novel mixed signal separation algorithm for cognitive radio networks that helps eliminating and banning hostile terminals that may violate the spectrum sharing policy in the network.

This mixed signal separation operates in three stages: the fist one is a frequency edge location algorithm that helps locating where the malicious communication operates in the wide band spectrum. Then, the second stage consists of a blind source separation like solution adapted to cognitive radio problem. And finally, in order to infer which of the resulting signals is the hostile one, a cyclostationary feature detection technique is applied to the resulting signals to determine on to which standard they do belong.

Finally, we gave some simulation results about the proposed technique in terms of probability of correct classification of the hostile signal versus signal to noise ration.

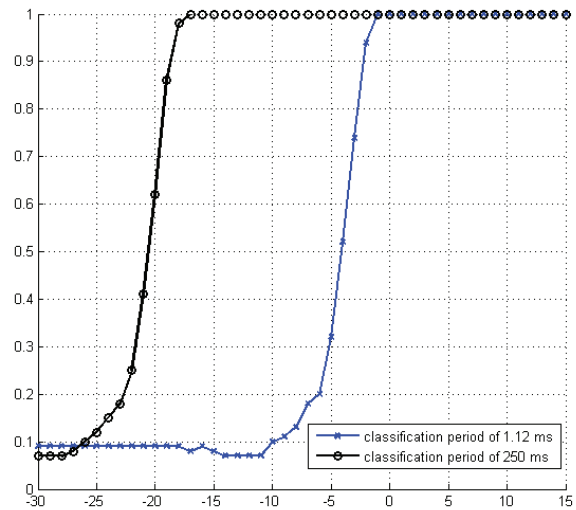

Fig. 2. Probability of right classification Vs. SNR for the simulated scenario

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