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Blind Source Separation-based Full-Duplex Cognitive Radio

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***Abstract*—Full-Duplex has been emerged in Cognitive Radio Network in order to avoid the silence period of the Secondary User (SU) during the Spectrum Sensing. SU should monitor the Primary User (PU) activities in order to avoid any harmful interference. The conventional Full-Duplex Cognitive Radio (FD-CR) systems are based on the Self-Interference Cancellation, where a problem of Residual Self-Interference and Hardware Imperfections leads to an important loss in the detection performance. In this paper, we develop spectrum sensing techniques for FD-CR based on the Blind Source Separation (BSS). In BSS, multi receiving antennas are required to detect the presence of the Primary User (PU) signal without the need for a silence period during the spectrum sensing. This fact enhances the data rate of the SU. In addition, this algorithms do not require any priori knowledge about the SU or the PU signal. Experimental results show that in addition to eliminating the silence period, the performance of our developed algorithms based on BSS outperforms the classical spectrum sensing Energy Detector (ED).**

Keywords*—Cognitive Radio, Spectrum Sensing, Blind Source Separation, Full-Duplex, Half-Duplex

I. Introduction

In classical Cognitive Radio (CR) system, Primary User (PU) and Secondary User (SU) can share the same frequency band but not simultaneously. SU can operate on this frequency band only when PU is absent in order to avoid any interference. For this reason, SU should monitor the PU activity continuously by performing the Spectrum Sensing. Spectrum Sensing provides CR with the PU status: active or idle. During the Spectrum Sensing, SU stops the transmission in order to do not affect the sensing decision by the Self-Interference (SI). For this reason, classical CR is called Half-Duplex CR (HD-CR) in which the activity period of SU can be divided into two slots, the first one is allocated to the Spectrum Sensing and the second one for the transmission. In the first slot when SU detects a PU transmission, then SU should immediately vacate the channel, else, SU continues to the second slot and operates on the channel. The silent period of SU during the Spectrum Sensing period affects the SU data rate [1], [2].

Full-Duplex Cognitive Radio (FD-CR) has been recently proposed as a promising solution to cancel the silent period of the Secondary User (SU) [1], [3], [4], [5], [6], [2]. Based on the recent advances in the Self-Interference Cancellation (SIC) [7], FD-CR has gained a lot of attention during the last years. FD-CR concerns mainly the Spectrum Sensing, where this approach is based on the elimination of the SU received signal on the SU receiving antenna (R_X). In fact, SU has a perfect knowledge on its signal transmitted from its transmitting antenna (T_X). After estimating the channel between T_X and R_X, SI is cancelled by regenerating an estimation of the SU received signal using the channel estimation, and subtract it from the overall received signal. In fact, in addition to the non-perfect estimation of the channel, the hardware components do not work perfectly. Many imperfections are presented in both the transmitting and the receiving circuits. Even the residual of SI and the hardware imperfections related to the SI signal are of negligible power compared to SI signal, they are of important power compared to the PU signal. This is due to the short distance between T_X and R_X which implies a very high received SI power.

In Full-Duplex communication, the residual of SI and the hardware imperfections are assumed to be acceptable if their power level becomes equal to that of the noise. This condition is not sufficient in Spectrum Sensing, since such level of power may deteriorate the Spectrum Sensing performance. In fact, in [8], we treated the performance of the energy detector in both HD and FD modes. In addition, we rely the performance of ED in FD mode to that in HD mode. As results, we obtain that for a loss of only 10 % (i.e. detection rate in FD mode = 90 % of the detection rate in HD mode for the same false alarm rate), the RSI should be 7 dB bellow the noise level. Accordingly, the lower the loss the lower the RSI power.

Such level of RSI power is very difficult to be achieved, keeping the Spectrum Sensing performance efficient in FD-CR is very important to CR in order to remain reliable. In addition, FD-CR using SIC means that the asymptotic performance of Spectrum Sensing in FD mode is the performance under HD mode.

The BSS techniques have been introduced in CR in order to avoid the silence period during the spectrum sensing [9], [10]. BSS consists in the separation of N independent sources based on M observations (Generally M $\geq$N) [11]. Since the PU and SU signals are independent, the BSS can be used in this context. Once the separation is achieved, a test of kurtosis can be carried out on the separated signal in order to make a decision on the presence of PU [10], [12].

Unlike [10], [12], where the kurtosis test is only considered, the separated signals are tested using different spectrum sensing algorithms a Goodness of Fit (GoF) [13] and autocorrelation (AC) tests [14] will be applied on the separated signals.

On the other hand, due to the spatial diversity where a long distance between the M receiving antennas and the transmitting antenna relative to conventional FD systems, the power of the SU received signal copies does not dominate the PU signal power. Further, the hardware imperfections become negligible since they are related to the SU signal power.

II. Local and Distributed Spectrum Sensing

Whatever the CR is HD or FD, its architecture may be local or distributed [15]. In local CR, Spectrum Sensing makes the decision of the channel availability based on its individual observation for the channel. This type of sensing is vulnerable to several problems such as the channel fading, shadowing, *etc*, which make PU hidden for SU. This fact makes local Spectrum Sensing not reliable enough. To solve this problem, distributed Spectrum Sensing has been proposed. In such architecture, several SUs are cooperating in order to make a decision on the PU status. The cooperation can be made using one of the three following strategies: 1) Hard Combining Scheme (HCS) [15], [16] a Fusion Center (FC) combines the decisions of SUs on the PU activity. 2) Soft Combining Scheme (SCS) [16]: Each SU sends to FC a Test Statistic (TS) evaluated based on a Spectrum Sensing algorithm (All the SUs use the same algorithm), then FC combines these TSs and then make a decision. 3) Observation Combining Scheme (OCS) [17]: The SUs send their observations to FC, where they are processed an then a decision is made based on the processed data. Distributed Spectrum Sensing may avoid the hidden PU problem due to the spatial diversity. Since BSS needs several observations to perform the signal separation, then it can be a good candidate to perform the distributed Spectrum Sensing.
In BSS, SUs are not interesting by the SIC, but they send their observations to a FC where an technique of signal separation is done. The channel availability is examined based on the characteristics of the separated signals.

III. Blind Source Separation for Spectrum Sensing

The use of BSS in spectrum sensing was initially proposed in [9], the advantage of BSS techniques is their ability to sense the channel even if the SU is operating. In addition, those techniques don't require any prior information about the signals. However, BSS assumed the statistical independence of the sources. The latter assumption can be satisfied in spectrum sensing since the PU signal and the SU are independent.

A. Narrowband Spectrum Sensing

When saying Narrowband, we mean that the signal bandwidth is less than the channel coherence bandwidth of the channel, then the channel can be considered as flat. In BSS, such type of channels refers to the *Instantaneous Mixture*, in which, the observation at the receiving antenna is a linear combination of the signals forming the mixture.
In [10] and [12], the BSS is applied to Narrowband Spectrum Sensing using various BSS algorithms. One of the most widely used criterion in BSS-based Spectrum Sensing is the test of Gaussianity using the kurtosis of the separated signals. In our case, the noise is assumed to be i.i.d. Gaussian, but the signals are not.
In addition to the test of kurtosis to diagnose the status of the channel, we propose the use of other tests instead of the kurtosis: the autocorrelation and the Likelihhod Ratio goodness of fit (LLR GoF) tests. Note that Energy Detector cannot be applied in this context due to the scaling issue effected by BSS on the separated signals. However, let us consider the following model for Narrowband mixture:

$$Y(n) = GX(n) \tag{1}$$

where $Y(n) = \{y_1(n), y_2(n), ..., y_M(n)\}^T$ is the observed signal vector, $X(n) = \{x_1(n), x_2(n), ..., x_N(n)\}^T$ is the vector of the N source signals, and G represents the mixing matrix. It is well known, see [18], that the separation of a mixture can be done up to a permutation and a scalar. In the Spectrum Sensing context the permutation of the de-mixed signals is not a serious problem since the detector is looking only for the presence of the PU signal.
In our application, there are three sources, the PU signal, the SU signal and the Gaussian noise. Hence $Y(n)$ is the mixture received on M antennas with $M \geq 3$, and $X(n) = [x(n), s(n), w(n)]^T$.

B. BSS algorithms

In [10], [12], the Multi-User Kurtosis (MUK) and Fast Independent Component Analysis (FastICA) were used, where it was proved than MUK in more reliable than FastICA to perform the Spectrum Sensing. However, other algorithms will be test in this context to show their robustness. This may lead to enhance the Spectrum Sensing performance. A brief description of the well known Joint Approximation Diagonalisation of Eigenmatrices (JADE) algorithm and Generalized Eigenvalue Decomposition (GED) algorithm is presented.

1) JADE algorithm: It uses the Second Order Statistics (SOS) to whiten the observed signals, and High Order Statistics (HOS) are used to find a contrast function $\mathcal{J}$ satisfying the conditions of separation, see [19].

$$\mathcal{J} = \sum_i ||diag(WF(M_i)W^T)||^2 \tag{2}$$

where W is the separating matrix, $F(M_i)$ is the cumulant tensor of the matrix M_i. M_i can be chosen as the eigenmatrices of the cumulant tensor F [20]. The maximization of $\mathcal{J}$ leads to joint approximate diagonalization of $F(M_i)$, and then to find W: $\hat{Z}(n) = W^H Y(n)$, where $\hat{Z}(n)$ is the vector of estimated (separated) signals.

2) GED algorithm: In [21], the BSS was formulated as a generalized eigenvalue decomposition (GED) problem, when the signals are non-gaussian, non stationary or non-white. In fact, the covariance matrix R_Y of the observations is given by:

$$R_Y = GR_XG^H \tag{3}$$

Where R_X is the covariance matrix of the sources, which is assumed to be diagonal thanks to the independence property of the sources. For non-Gaussian, non stationary or non-white signals, the authors of [21] proved that there exist another cross-correlation matrix Q_Y of the same diagonalization property of R_X:

$$Q_Y = GQ_XG^H \tag{4}$$

Based on equations (3) and (4) and by exploiting the relation of the ideal separation: $X(n) = W^H GX(n) = W^H Y(n)$, one can obtain the following relation:

$$R_Y W = Q_Y W \Lambda \tag{5}$$

where $\Lambda = R_X Q_X^{-1}$ is a diagonal matrix [21]. Equation (5) constitutes a generalized eigenvalue equation, which can determine the unmixing matrix W.

C. Test performed on the estimated sources

Once the separation is achieved, a test of existence should be carried out on the estimated signals to perform the spectrum sensing. The sensing of the channel can be done under two situations according to the SU state during the Spectrum Sensing period: SU is transmitting, or SU is inactive.
In our study, we consider that the sensing can be performed while the SU is active.
In this paper, we assume that PU exists if the following equation is satisfied:

$$\sum_{i=1}^{3} I(\xi_i > T) \geq 2 \tag{6}$$

Where I is the logic test function that outputs 1 if the test is true and 0 elsewhere, the metric $\xi_i,\ i = 1, 2, 3$ is obtained after applying a test $\mathcal{T}$ that aims to distinguish between noise signal or modulated signal, and T is a threshold to be fixed according to $\mathcal{T}$. Equation (6) means that at least two of the three separated signals satisfy the test $\mathcal{T}$. In this paper, we introduce two new tests, the autocorrelation test, and the LLR GoF test. The previously proposed Kurtosis test is well detailed in [10].

1) Autocorrelation test: Instead of using the Gaussianity, the autocorrelation tests the whiteness of the separated signals. The autocorrelation test can be applied on baseband signals. Based on the fact that the PU and SU use the same carrier, the spectrum sensing can be performed using the baseband signals. The PU and SU signals are assumed to be over-sampled with a factor T_0 [14], therefore $s(n)$ can be formulated as follows:

$$s(n) = \sum_k s_k q(n - kT_0) \tag{7}$$

Where $q(n)$ is the emission filter, $\{s_k\}$ are the symbols to be modulated, which are assumed to be i.i.d., and T_0 is the symbol period. This fact makes the autocorrelation $\rho_s(m)$ of $s(n)$ non zero for a lag $m < T_0$ (the same for $x(n)$). The autocorrelation $\rho_s(m)$ can be written as follows [22]:

$$\rho_s(m) = E[s(n)s^*(n-m)] = \sigma_s^2(1 - m/T_0) \tag{8}$$

When the test of equation (8) is applied on the noise, we obtain $\rho_w(m) = \sigma_w^2 \delta(m)$, since the noise is assumed to be white.
The test of autocorrelation $\rho_i(m),\ m > 0$, is applied on each of the three estimated signals after the BSS process, if $\sum_{i=1}^{3} I(\rho_i(m) > T_\rho) \geq 2$, where T_ρ is a predefined threshold, then we have at least two modulated signals (SU and PU signals), and then PU exists.

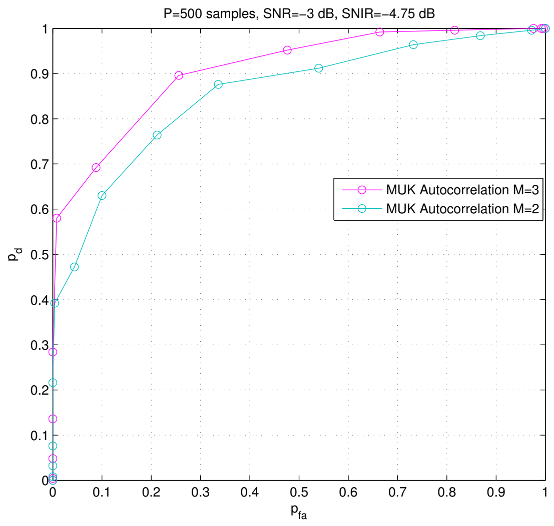

Fig. 1. Performance under two situations : a) the noise is not considered as a signal, and b) the noise is considered as a signal

2) LLR χ^2 goodness of fit test: Since the noise is supposed to be Gaussian and complex in general, and $w(n) = w_r(n) + jw_i(n)$, the norm two of $w(n)$ $||w(n)||^2$ follows a χ^2 distribution of degree of freedom 2. In [13], a LLR GoF test based on χ^2 (LLR χ^2) is proposed in spectrum sensing, this algorithm requires a silence period. In our context, we would like to apply this test on the three separated signals by finding the metric Θ_i [13] for each of the estimated signals.

$$\Theta_i = -\sum_{i=1}^{P} \left(\frac{ln(F_0(\hat{z}_i(n)))}{P - i + 1/2} + \frac{ln(1 - F_0(\hat{z}_i(n)))}{i - 1/2} \right) \tag{9}$$

where $\hat{z}_i(n)$ is the *ith* separated signal, and F_0 is the CDF of χ^2 distribution. A value of Θ_i that is greater than a predefined threshold means that a non-Gaussian signal is presented. If $\sum_{i=1}^{3} I(\Theta_i \geq T_\Theta) \geq 2$, then the PU exists, where T_Θ is a predefined threshold.

D. Number of required receiving antennas

According to the number of existing sources, $s(n)$, $x(n)$ and $w(n)$, a BSS technique has to separate three signals. In [10] and [12], the noise is not taken in account, and the number of signals is assumed to be two: PU signal and SU signal. In fact, this assumption affects the BSS performance in spectrum sensing. Figure 1 shows the result of the simulations under the two situations: a) Without the noise and b) when the noise is considered as a third signal. In (a) the number of required receiving antennas is two at least, whereas under (b) the number is three. The MUK algorithm is used, and a test of autocorrelation is carried out on estimated signals. It is clear that the performance under situation (b) outperforms that under situation (a). For example, under situation a) $p_d = 0.9$ is acheived for $p_{fa} = 0.25$; whereas under (b), this probability is achieved for $p_{fa} = 0.47$.

E. Wideband Spectrum Sensing

For Wideband signals, the channel is no longer flat, and the instantaneous mixture do not reflect the combination of the signals at the receiving antennas. In this situation, the received mixture at each receiving antenna is composed from filtered copies of the signals to be detected, where the channel plays the role of a filter. In this case the mixture is called *convolutive*. The algorithms that can perform the BSS for convolutive mixture are much more complicated than those performing BSS of instantaneous one. In general, when the mixture becomes convolutive, the robustness of the separation process decreases. In addition, the test of a wideband as a one frequency portion may lead to loss spectrum opportunities since white space may exist inside an occupied wideband. An example on this situation is the sparse frequency bands. In addition, many technologies based on Multicarrier modulation, such as WiFi and WiMax left some subcarrier without data allocation. These subcarriers can be used by SU without causing interference to PU. Consequently, we advise to divide the Wideband into several Narrowbands on which the signal separation is performed. This divisions operations makes CR more aware to the white space in its radio environment and allows it to exploit efficiently the white spaces. Of the BSS point of view, the instantaneous mixture is now applicable, since the division of the Wideband into Narrowband makes the channel flat relative to each Narrowband.

In OFDM-based transmission, the FFT operation at the receiver provide the BSS system with the ability to sense each sub-band as narrowband. In fact, when assuming that the OFDM symbol is composed from N_s subcarrier, the FFT operation results in N_s samples, in which the ith one represents the data transmitted at the ith subcarrier. After receiving N OFDM symbols, the BSS is then applied on the sub-band B_i containing N samples. Applying BSS on each B_i results on detecting the spectrum holes even if a SU is active on that B_i. For that reason, we assume that a Fusion center (FC) performs the BSS based on the observation of M SUs, with $M \geq 3$. SUs involved in the BSS are not active, so they receive the PU signal, the SU signal and the noise.

IV. Simulation Results

In order to test the efficiency of our proposed algorithms, Monte-Carlo simulations were conducted to show the ROC curve of various techniques proposed in this paper. The channels between PU base station and the SU transmitting antennas, from one hand, and the SU receiving antennas, from other hand, are assumed to be flat fading Rayleigh channel.

The simulations are done with a SNR of SU of -10 dB. PU signal is assumed to have the same power as SU signal at the receiving antenna.

Regarding SIC-based FD-CR, the residual power of the SU signal is assumed to be as the same as the noise power.

Figure (2) shows the performance of the classical energy detector under FD and HD modes. Under FD mode, the energy detector performance is highly degraded due to the residual SI power.

On the other hand, figures (3), (4) and (5) show the simulations results of the proposed BSS algorithms, MUK,

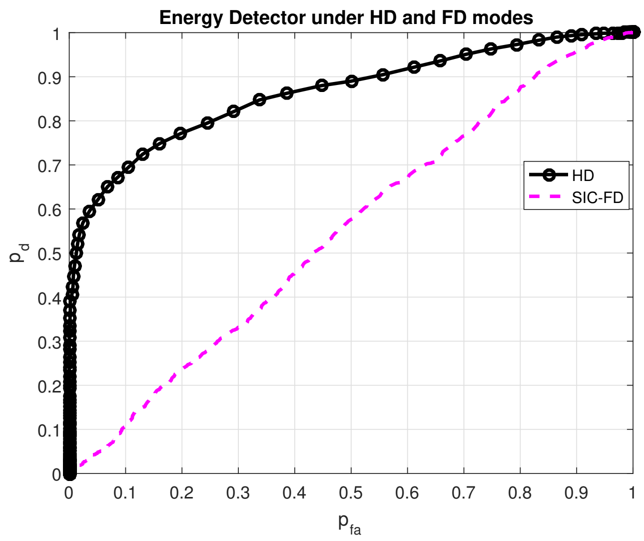

Fig. 2. Performance of the classical spectrum sensing Energy Detector under FD and HD

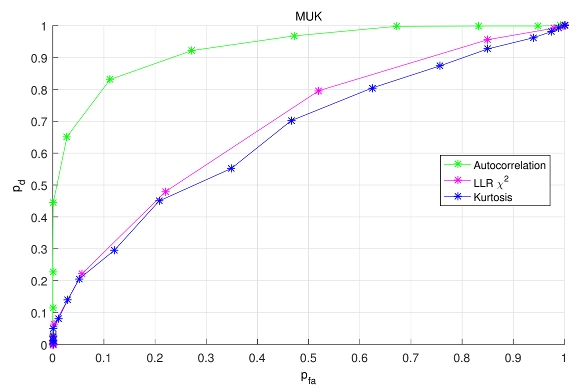

Fig. 3. Spectrum Sensing performance: MUK

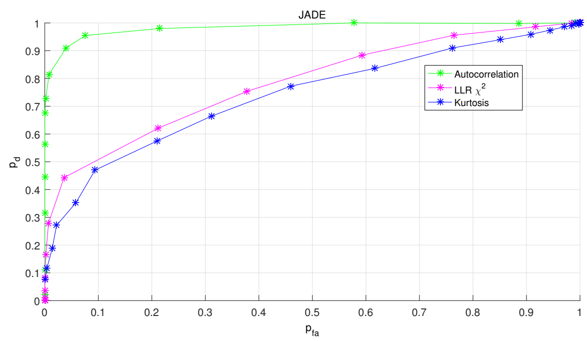

Fig. 4. Spectrum Sensing performance: JADE

JADE and GED, for $N = 1000$ samples, and a number of receiving antennas $M = 3$. For the various algorithms, the autocorrelation and LLR χ^2 tests outperform the existing kurtosis test. In addition, JADE outperforms GED and MUK for the various tests used in this paper, whereas GED outperforms MUK for the autocorrelation test, and it has approximately the same performance as MUK when the LLR χ^2 and the kurtosis tests are used.

On the other hand, JADE with autocorrelation detector outperforms the classical energy detector in HD mode, thus fact

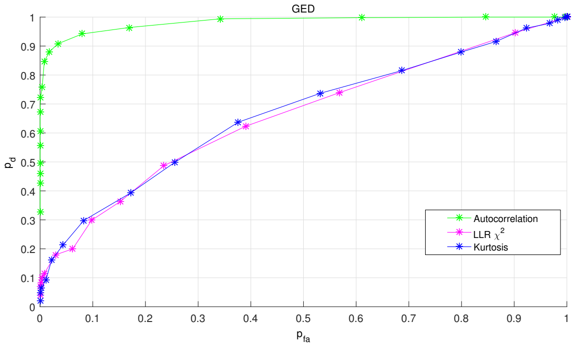

Fig. 5. Spectrum Sensing performance: GED

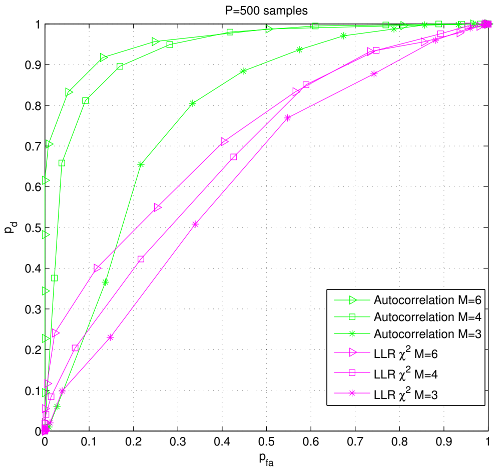

Fig. 6. Performance of JADE algorithm for different numbers of receiving antennas

means that BSS leads to enhance the detection performance as well as the data rate of SU (performing the spectrum sensing and the transmission simultaneously).
Figure (6) shows the performance of JADE algorithm with autocorrelation and LLR χ^2 tests for different number of antennas M. The number of samples is set to $P = 500$. The simulation results show that the performance of both autocorrelation and LLR χ^2 tests becomes more robust while M increases. Under all these situations, the autocorrelation test outperforms the LLR χ^2 test.

V. Conclusion

In this paper, Blind Source Separation (BSS) is proposed to perform the Full-Duplex Cognitive Radio (FD-CR) in order to enhance the Secondary User data rate. Several BSS algorithms have been tested with several detections algorithms in order to illustrate the BSS performance in FD-CR. Even though BSS algorithms need multi-antenna system, their performances for the different tested algorithms show their robustness where the silent period of SU is avoided. In addition, an enhancement of the detection is gained compared to the energy detector in Half-Duplex mode which is considered as the asymptotic case of the conventional Full-Duplex mode.

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