BLIND CARBON COPY ON DIRTY PAPER: SEAMLESS SPECTRUM UNDERLAY VIA CANONICAL CORRELATION ANALYSIS

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ABSTRACT

The spectrum underlay concept promises enhanced spectrum utilization without disturbing legacy / licensed or scientific primary users, so long as their interference constraints can be met. Existing underlay schemes assume that both the primary signal to secondary interference plus noise ratio, and the secondary signal to primary interference plus noise ratio can be high enough at the primary and secondary receiver, respectively. Even if the cross-network channel state information is available at the secondary users, these two conflicting requirements are hard to achieve simultaneously in practice. This work proposes a practical data-driven approach that allows a pair of secondary users to reliably communicate in underlay mode while keeping the interference at the primary receiver close to its noise floor. The secondary transmitter merely has to transmit its signal twice, at very low power - above the noise floor, but well below the primary's interference. It is shown here that reliable detection of the secondary signal is possible via canonical correlation analysis (CCA). Theoretical and experimental results reveal the remarkable detection performance of the proposed CCA-based approach, which does not require any cross-network coordination, or even channel state information.

1. INTRODUCTION

Dynamic spectrum access techniques hold promise for significantly improved spectrum utilization on-demand and by allowing secondary unlicensed users to take advantage of ephemeral transmission opportunities in space, time, or frequency [1, 2]. Among several dynamic spectrum access modalities [1], underlay spectrum sharing is very appealing in terms of prioritization of licensed and scientific 'legacy' uses, spectrum utilization efficiency, and practical feasibility – since it allows coexistence without need for coordination between the two user 'tiers'.

Although there is a plethora of work done on underlay cognitive radio networks (CRN) in the literature [3–7], these works assume that the signal to interference plus noise ratio (SINR) at the secondary receiver is relatively high. In practice, this is very hard to ensure while protecting the primary user(s) – especially scientific instruments such as weather radar, or radio-telescopes which are extremely sensitive. Furthermore, all of these works are relying on assumptions that are hard to meet – such as the availability of cross-channel knowledge at the secondary users. The authors of [3], however, have recently proposed a nice semi-blind beamforming-based underlay spectrum sharing approach, which allows the secondary users to access the spectrum while minimally affecting the primary network performance, without requiring any channel knowledge at the secondary network. However, the proposed method in [3] requires i) the primary communication to be bidirectional (which does not hold for legacy radio/TV broadcast, or scientific uses); ii) the flow direction of primary traffic to be predictable; iii) effectively time-invariant channels from/to the primary users; and iv) training pilots for designing the beamformer at the secondary receiver. These are still restrictive assumptions. In particular, the reverse transmission of the primary user needs to be synchronized with the forward of the secondary, and vice versa, so the secondary users need to track which node is transmitting in the primary network.

Is it possible to design an underlay strategy that enables reliable decoding at very low SINR and modest SNR at the secondary receiver, without noticeable increase of the noise floor at the primary receiver? Is it possible to do this seamlessly, without any coordination between the primary (legacy / incumbent) and the secondary user?

This is the holy grail of secondary spectrum access and seamless cohabitation, but is it a realistic objective? The answer is, surprisingly, affirmative. This paper proposes a secondary transmission scheme that operates at very low power yet allows reliable secondary communication without requiring any channel knowledge or coordination with the primary system. The proposed scheme is (in a way) reminiscent of an information-theoretic multicast scheme that was proposed years ago under the name *carbon copy on dirty paper* [8], following the classic dirty paper coding work of Costa [9]. However, the proposed scheme is also fundamentally different than the one in [8], in that the latter assumes non-causal deterministic knowledge of the interference at the transmitter, whereas the scheme proposed herein does not – it is fully *blind*, and for this reason it is named *blind carbon copy on dirty paper* – the analogy will be made clear soon.

In the proposed scheme, the secondary transmitter sends its signal *twice*, each time at very low power. This allows creating two "views" of the signal space that only share the secondary signal – the interference from the primary system is potentially very strong, but different in the two views. Invoking canonical correlation analysis (CCA) on these two views, a secondary receiver which employs two receive antennas can reliably decode its intended signal, under very strong inter-

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ference from the primary user. This is shown both theoretically and numerically. In particular, it is shown that the proposed CCA method can reliably decode the secondary user signal at very low SINR (e.g., -45 dB) at the secondary receiver. Furthermore, experimental results reveal that the proposed CCA method approaches the detection performance of the state-of-the-art methods operating in the interference-free regime (where the primary users are idle).

CCA is a widely-used statistical learning tool that seeks to find linear combinations of two random vectors such that the resulting pair of random variables is maximally correlated [10]. In recent work [11], the authors came up with a new and broadly useful algebraic interpretation of CCA as a method that can identify a common (shared) subspace between two multivariate signals. CCA has found many other applications in signal processing and wireless communications, including direction-of-arrival estimation [12], equalization [13], radar [14, 15], blind source separation [16], and more recently cell-edge user detection [11], and multi-view learning [17–19], to name a few.

2. SYSTEM MODEL AND PROBLEM STATEMENT

Consider an underlay cognitive radio network comprising one secondary transmitter (STx) communicating with a secondary receiver (SRx) equipped with $N_s \geq 2$ antennas, in the presence of a primary transmitter (PTx) and primary receiver (PRx) with $N_p \geq 1$ antennas, as shown in Fig. 1 (more than one PRx can be accomodated). Let $\mathbf{h}_s \in \mathbb{C}^{N_s}$, $\mathbf{h}_{ps} \in \mathbb{C}^{N_s}$, $\mathbf{h}_{sp} \in \mathbb{C}^{N_p}$ and $\mathbf{h}_p \in \mathbb{C}^{N_p}$ be the channel response between the STx and SRx, PTx and SRx, STx and PRx, and PTx and PRx, respectively, defined as

$$\begin{aligned} \mathbf{h}_s &= \sqrt{\sigma_s}\,\mathbf{g}_s, \quad \mathbf{h}_{ps} = \sqrt{\sigma_{ps}}\,\mathbf{g}_{ps}, \\ \mathbf{h}_p &= \sqrt{\sigma_p}\,\mathbf{g}_p, \quad \mathbf{h}_{sp} = \sqrt{\sigma_{sp}}\,\mathbf{g}_{sp} \end{aligned} \tag{1}$$

where $\mathbf{g}_s$, $\mathbf{g}_{ps}$, $\mathbf{g}_{sp}$ and $\mathbf{g}_p$ are the respective small-scale fading vectors while the terms $\sigma_s, \sigma_{ps}, \sigma_{sp}$ and σ_p are the corresponding large scale fading coefficients with values dependant on the propagation distance and environment. Unlike prior works [3–7] that rely on the assumptions that perfect knowledge of the cross channels $\mathbf{h}_{ps}$ and/or $\mathbf{h}_{sp}$ is available at the secondary receiver and the secondary transmitter, respectively, this paper assumes that the secondary users have no knowledge about any channel state information in the network.

The goal of this work is to show that, without any coordination between the secondary and primary systems, the secondary user can *reliably* communicate without harmfully affecting the primary user's performance. To do so, we will next present a simple spectrum sharing scheme together with a data-driven (unsupervised learning-based) approach that allow i) the STx to transmit its signal at very low power so that it does not affect the detection performance at the PRx, keeping the resulting interference close to its noise floor, and ii) the SRx to reliably decode its intended signal at significantly low SINR as we will verify later. Note that we consider one primary transceiver and one secondary transceiver for clarity of exposition. Multiple primary and secondary users can be accommodated, but require more space and more sophisticated transmission and reception schemes. We therefore reserve such scenarios for future publications.

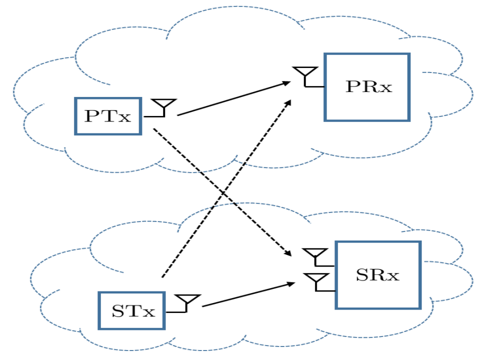

Fig. 1: System Model

3. SECONDARY TRANSMISSION SCHEME

In this section, we will present a simple practical scheme for the secondary transmitter so that it can reliably communicate with its receiver over the same channel occupied by the primary network, and without degrading the PRx performance. Define $\mathbf{s} \in \mathbb{C}^N$ as the transmitted signal from the STx (our proposed approach also works with analog signals). The secondary transmission scheme is described as follows.

The STx transmits the same sequence (denoted by $\mathbf{s}$) *twice* at *very low* power – so that it is received above the thermal noise floor at the SRx, but far below what is required to be directly decoded in the face of possibly overwhelming interference by the primary user. The repetition of the secondary user sequence can happen at the symbol or block level; we assume here block-repetition for simplicity of exposition. Towards this end, the discrete-time baseband-equivalent model of the received signal, $\mathbf{Y} \in \mathbb{C}^{N_s \times 2N}$, at the secondary receiver is

$$\mathbf{Y} = \sqrt{\alpha_s}\mathbf{h}_s\mathbf{x}_s^T + \sqrt{\alpha_p}\mathbf{h}_{ps}\mathbf{x}_p^T + \mathbf{W} \tag{2}$$

where $\mathbf{x}_s = [\mathbf{s}^T, \mathbf{s}^T]^T \in \mathbb{C}^{2N}$ is the overall transmitted signal by the STx after repetition, $\mathbf{x}_p \in \mathbb{C}^{2N}$ is the transmitted signal by the PTx, and α_s and α_p denote the transmission power of the STx and the PTx, respectively. The term $\mathbf{W} \in \mathbb{C}^{N_s \times 2N}$ contains independent identically distributed elements with each entry drawn from a complex Gaussian distribution with zero mean and variance N_0. We will next present a low-complexity learning-based approach that will allow the SRx to reliably decode its intended signal, $\mathbf{s}$, even if the received SINR is significantly low.

Remark 1. *It is worth pointing out that if the primary user signal is order(s) of magnitude stronger, then one can cancel the primary interference by simply projecting the received signal on the minor left singular vector of the matrix* $\mathbf{Y}$*, thereby "revealing" the secondary transmission. This can only work when the spatial channels of the two users are time-invariant. In practice, the channel gains fluctuate over time, and even if the average secondary signal to interference ratio is low (e.g., -40 dB), there are times when it becomes relatively high (e.g., -20 dB). These fluctuations quickly degrade the subspace estimate, leading to complete failure to detect the secondary signal.*

Remark 2. *We point out that the proposed transmission scheme can be interpreted as repetition coding, or equivalently, as spreading the secondary user's transmission with spreading gain equal to 2 [20]. Treating this situation as CDMA or as an error control problem will not work, because the primary user dominates the received signal, and small spreading / coding gains cannot make up for the large power difference between the secondary and primary user.*

4. SECONDARY SIGNAL DETECTION VIA CCA

By partitioning $\mathbf{x}_p^T = [\mathbf{p}_1^T \mathbf{p}_2^T]$ in two blocks, and by exploiting the repetition structure, the SRx can split $\mathbf{Y}$ and $\mathbf{W}$ into two blocks, $\mathbf{Y} = [\mathbf{Y}_1 \ \mathbf{Y}_2]$, and $\mathbf{W} = [\mathbf{W}_1 \ \mathbf{W}_2]$, for which we have

$$\mathbf{Y}_1 = \mathbf{H}_s \left[\mathbf{s}, \mathbf{p}_1\right]^T + \mathbf{W}_1 \tag{3}$$

$$\mathbf{Y}_2 = \mathbf{H}_s \left[\mathbf{s}, \mathbf{p}_2\right]^T + \mathbf{W}_2 \tag{4}$$

where $\mathbf{H}_s \in \mathbb{R}^{N_s \times 2}$ is the channel matrix holding in its columns the channel vectors $\mathbf{h}_s$ and $\mathbf{h}_{ps}$. Furthermore, the transmit power terms of both the STx and PTx have been absorbed in the respective channel vectors, for brevity. Now, given the two signal views in (3) and (4), CCA will be invoked to show that reliable detection of the secondary signal, $\mathbf{s}$, is possible even at low SINR. To see how we can utilize CCA to identify the secondary signal, $\mathbf{s}$, from $\mathbf{Y}_1 \in \mathbb{C}^{N_s \times N}$ and $\mathbf{Y}_2 \in \mathbb{C}^{N_s \times N}$, we will use the so-called *maximum variance* (MAX-VAR) formulation of CCA [21]. That is,

$$\min_{\mathbf{g}, \mathbf{q}_1, \mathbf{q}_2} \sum_{\ell=1}^{2} \|\mathbf{Y}_\ell^T \mathbf{q}_\ell - \mathbf{g}\|_F^2 \tag{5a}$$

$$\text{s.t.} \quad \|\mathbf{g}\|_2^2 = 1 \tag{5b}$$

The above problem seeks to find a direction $\mathbf{g} \in \mathbb{C}^N$ that is maximally correlated after the linear projections of $\mathbf{Y}_1$ and $\mathbf{Y}_2$ on $\mathbf{q}_1 \in \mathbb{C}^{N_s}$ and $\mathbf{q}_2 \in \mathbb{C}^{N_s}$, respectively. An appealing feature of CCA that adds to the simplicity of the overall approach and renders it favorable from the practical point of view is its computational complexity. It has been shown in [22] that problem (5) admits a simple algebraic solution via eigendecomposition, so solving (5) is tantamount to solving for the principal eigenvector of a matrix involving the sample auto- and cross-covariance matrices of two random vectors each of size $N_s \times 1$.

In a recent work [11], we have shown that given two multi-antenna signal views that include one shared (common) component and multiple individual ("private", not shared) components in each view, then CCA can efficiently extract the common component up to scaling ambiguity no matter how strong the individual components are. One can see from (3) and (4) that each block (view) is subject to strong interference by the primary user, *but the interference is different in the two blocks* – thus there is a unique common subspace, namely (the span of) $\mathbf{s}$ that conveys the secondary transmission. Building upon our theoretical findings in [11], we will next show that our CCA interpretation applies, and under very mild conditions will recover $\mathbf{s}$ up to scaling, even if $\mathbf{p}$ is several orders of magnitude stronger than $\mathbf{s}$.

The following theorem, which is a slight modification of the results of [23], states the conditions for identifying the secondary transmitted signal $\mathbf{s}$ at the SRx.

Theorem 1. *In the noiseless case, if the matrices $\mathbf{X}_\ell := [\mathbf{s}, \mathbf{p}_\ell] \in \mathbb{C}^{N \times 2}$ and $\mathbf{H}_s \in \mathbb{C}^{N_s \times 2}$ are full column rank for $\ell \in \{1, 2\}$, then the optimal solution $\mathbf{g}^\star$ of problem* (5) *is given by $\mathbf{g}^\star = \gamma \mathbf{s}$, where $\gamma \in \mathbb{C}$, $\gamma \neq 0$ is the scaling ambiguity.*

Proof. The proof is provided in Theorem 1 in [11]. □

Note that the full rank condition on the matrices $\mathbf{X}_\ell$ needs the signals $\mathbf{s}$ and $\mathbf{p}_\ell$ to be linearly independent which is practically always the case for any reasonable "packet" length N, because these signals are drawn from statistically independent sources. On the other hand, the full rank condition on $\mathbf{H}_s$ is in fact the more restrictive one as it requires i) the number of antennas at the SRx to be $\geq$ to the number of co-channel signals (two in our setting) and ii) the channel vectors to be linearly independent. The latter is realistic, these being statistically independent channel vectors from the PTx and the STx to the SRx.

Remark 3. *Although* (3) *and* (4) *implicitly assume that that the channel is constant across the two secondary repetition blocks, our proposed method in fact can work even if the two channel matrices are different [11]. Therefore, with block repetition, the coherence time needs to be only greater than one block duration.*

5. NUMERICAL RESULTS

In this section, we provide simulation results to assess the performance of the proposed CCA approach. We consider the underlay scenario shown in Fig. 1. The transmit power at the PTx, α_p, is set to 25 dBm while the maximum transmit power at the STx, α_s, is set to 6 dBm. The large scale fading parameters (path-loss) used in the simulation are set to $\sigma_s^2 = -85$ dB, $\sigma_{sp}^2 = \sigma_{ps}^2 = -80$ dB, and the additive white Gaussian noise power is set to $N_0 = -90$ dBm. The small scale fading parameters are modeled as circularly symmetric Gaussian random variables with zero mean and unit variance. It is assumed that the SRx has two antennas, unless stated otherwise. Furthermore, the total number of samples collected at the SRx is assumed to be 1024, so the repetition is done over two blocks, each of length 512 samples. We conducted 10^4 Monte-Carlo two-block-transmission experiments, each time drawing new $\mathbf{s}, \mathbf{p}, \mathbf{W}$ and $\mathbf{H}_s$.

Since we assume digitally-modulated symbols at the secondary user, we will use the bit error rate (BER) as a performance metric (but recall that our method can also work with analog transmissions). Furthermore, to benchmark our proposed method, we will use the singular value decomposition (SVD) of the matrix $\mathbf{Y}$ to estimate the channel direction during a period when the primary user is inactive, i.e., there is no interference from the primary user. Then, the secondary user signal can be estimated by projecting the received signal $\mathbf{Y}$ on the principal left singular vector. In order to resolve the scaling ambiguity that is inherent both in the proposed CCA method

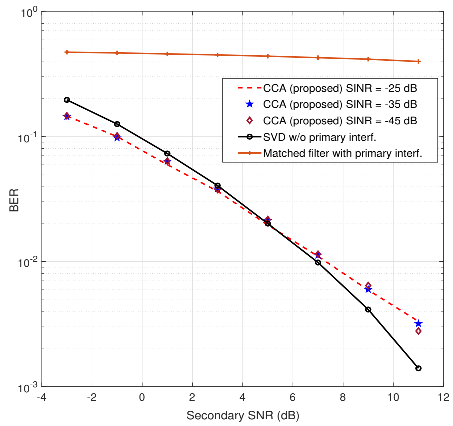

Fig. 2: BER vs. SNR of the secondary user at three levels of secondary SINR.

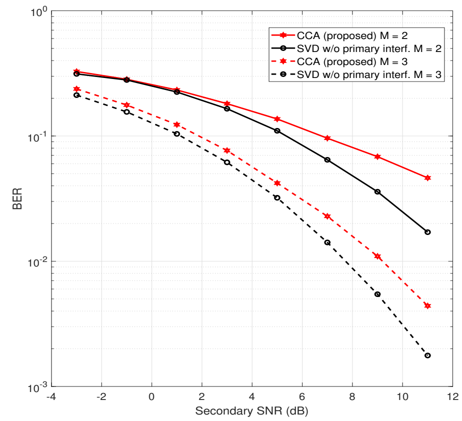

Fig. 3: BER vs. secondary user SNR for different number of antennas at the SRx.

and the SVD-based baseline, we assume that the first bit of $\mathbf{s}$ is $+1$.

In the first experiment, we studied the detection performance of the secondary system with and without spectrum sharing. In order to illustrate the ability of our proposed approach to correctly decode the secondary transmission at very low SINR, we varied the STx power from -8 dBm to 6 dBm which corresponds to the received SNR range in Fig. 2. For each value of the secondary SNR, we report the corresponding BER obtained by our proposed CCA method at three levels of the SRx SINR: from -25 dB to -45 dB. For this simulation, we assume that the PTx is sending a real analog signal with each sample drawn from a Gaussian distribution with zero mean and unit variance, while the STx is sending a BPSK signal. After solving the CCA problem (5), we averaged the two soft estimates of $\mathbf{s}$ obtained via $\mathbf{Y}_1\mathbf{q}_1$ and $\mathbf{Y}_2\mathbf{q}_2$, before hard thresholding. Fig. 2 depicts BER results obtained by our proposed CCA method for all three levels of primary interference, and the corresponding BER curve obtained using the SVD-based method at the same SNR *without any interference*. The results are pretty striking: CCA is remarkably insensitive to interference from the primary user, and it even outperforms the performance obtained using interference-free SVD in the low SNR region. In particular, under very strong interference from the primary user, our proposed method achieves approximately 1 dB SNR gain over the interference-free SVD-based method in the range $[-3, 3]$dB. This is in fact one of the most appealing features of the proposed CCA method. Note that the SVD-based method works better than our approach as the SNR increases, as expected. Finally, it is obvious that using matched filter assuming perfect knowledge of the secondary channel $\mathbf{h}_s$ at the SRx completely fails when the primary user is active (top orange line in in Fig. 1).

We now consider another experiment over the same SNR range, but this time we report the BER for different numbers of antennas at the SRx, assuming Gray coded QPSK transmission for both the STx and the PTx. Further, in this simulation the SINR at the SRx is -35 dB. In order to resolve the scaling ambiguity of both methods, we assume that that the first symbol is $(1+1j)/\sqrt{(2)}$. Fig. 3 shows that an order of magnitude reduction in the BER can be achieved by both methods when using three receive antennas at the SRx compared to two antennas. In particular, with three receive antennas, our method achieves 10^{-2} BER at 7 dB SNR while at the same time the resulting interference at the PRx is around its noise floor. Furthermore, it can be easily seen that our method is always approaching the SVD baseline operating without the primary user interference, and the gap between the two methods becomes even narrower by increasing the number of antennas.

Remark 4. *Note that our use of the SVD "baseline" without interference (which is more appropriately called an "oracle" method here) is purely to show how well the proposed method works – close to an oracle which operates in a fictitious interference-free environment. There is no real baseline method that we can use for comparison, because no other method (except ideal interference cancellation – which cannot work with an analog primary transmission or at medium SINR) can decode the secondary signal at this low SINR.*

6. CONCLUSIONS

In this paper, we proposed a low-complexity data-centric spectrum sharing approach for an underlay scenario with a pair of secondary users and a pair of primary users. The proposed method allows the secondary users to reliably communicate over the same channel occupied by the primary users, without any coordination, and without any channel state information. Our proposed solution is based on "repetition coding": the secondary user transmits its signal twice at very low power such that it does not affect the primary user detection performance. Constructing two signal views at the SRx and applying CCA to these views, we showed that the secondary receiver can reliably decode its intended signal at low SNR even if it is buried under strong interference from the primary user transmission. Numerical results demonstrated that our unsupervised CCA approach allows the SRx with two receive antennas to attain the same BER at -40 dB SINR as achieved by an SVD-based baseline in the interference-free case where the primary user is silent.

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