Experimental Evaluation of a Cooperative Kernel-Based Approach for Robust Spectrum Sensing

J. Manco-Vásquez, S. Van Vaerenbergh, J. Vía, I. Santamaría
Dept. of Communications Engineering, University of Cantabria, Spain

***Abstract*—The spectrum sensing accuracy has been improved by the introduction of cooperative spectrum sensing (CSS) strategies where the spatial diversity is exploited among non-legacy users. However, these CSS strategies also bring new impairments, such as the interference from other sources that severely degrade the sensing performance. In this paper, we evaluate experimentally our recent proposal for CSS based on kernel canonical correlation analysis (KCCA), where the effect of an interferer is also modeled. The experiments are conducted on a cognitive radio platform composed of several Universal Radio Peripheral (USRP) nodes, and the measurements show that our scheme is able of implicitly learning the surrounding environment by only exploiting the non-linear correlation among the receiver signals of each SU. Eventually, we provide comparative results where a considerable gain over a conventional energy detector is obtained in spite of the impairments provoked by external interferers.**

***Index Terms*—Cooperative Spectrum Sensing, Kernel Canonical Correlation, Cognitive Testbed, USRP.**

I. Introduction

Due to the enormous growth of wireless services, an efficient use of the spectral resources is required [1]. Cognitive Radio (CR) systems allows sharing the spectrum between incumbent or (PU) and non-legacy users or (SU). This technology relies on a spectrum sensing process that allows detecting exploitable holes in the spectrum that can be filled by subsequently transmissions of SU. A more reliable spectrum sensing is attained by CSS strategies that exploit the diversity among SU [2], and thus mitigating common impairments found in a local spectrum sensing such as multipath fading, shadowing and receiver uncertainty issues.

Although a SU may combine information from a database and local sensing to further decrease missed detections, these CSS strategies also brings new challenges to be overcome during the time that the channel remains idle. Interference, for instance, may come from local unintentional or intentional users as it is cataloged in [3]. The effect of misalignment among SU and impulsive noise during the sensing period are also studied in [4], and [5] respectively. Moreover, an energy detector is severely degraded in presence of interference [6], and its performance has been been recently improved by the introduction of machine learning techniques [7], where a set of feature vectors composed of energy levels is employed to train a classifier, after which it labels each new energy level as channel available or unavailable.

Despite of several approaches, few of them are also evaluated by means of experimental measurements [8]–[11]. In this paper, we extend some initial simulation results presented in [12], and present the experimental evaluation of a KCCA detector for CSS scenario, where the effect of external interference is also taken into account. The proposed scheme is able to learn the regions of decisions for the detection of the primary signal during a learning stage. It exploits the possible non-linear correlation among the measurements of energy reported by each SU, after which our KCCA detector applies them for online detection. It does not involve any parameter setting, and the detector can be retrained periodically to adapt itself to a changing environment. The measurements are conducted in platform consisting of several USRP nodes that emulate an scenario composed of a PU and several SUs, and the results shows that in spite of the interference caused by some SUs, the detection performance turns out to be more robust when employing our proposal.

The rest of the paper is organized as follows: In Section II, we give an overview of the CSS problem, a brief description of our KCCA detector is given in Section III. The scenario and the measurement setup are described in Section IV. We present the experimental results in Section V and finally, the paper concludes with a discussion of the obtained results in Section VI.

II. Cooperative Spectrum Sensing

Let us considering a scenario with M secondary users, in which interference is present under the null hypothesis. This problem can be formulated as,

$$\mathcal{H}_1 : p(r|\mathcal{H}_1) \neq \prod_{i=1}^{M} p_i(r_i|\mathcal{H}_1)$$
$$\mathcal{H}_0 : p(r|\mathcal{H}_0) = \prod_{i=1}^{M} p_i(r_i|\mathcal{H}_0)$$

where r_i denotes the received signal at each i-th SU, and r is a vector signal composed of all observations. We assume that r_i is conditionally independent under the null hypothesis, and not under the alternative hypothesis. In this way, a more general setting where a local and uncorrelated interference coming from different sources can be considered, while the primary signal under the alternative hypothesis may cover a large area

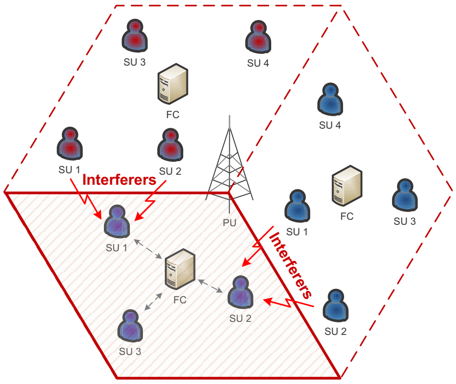


Fig. 1. A CSS in a heterogeneous network where interference from neighbour cells degrade the sensing performance.

where all SU are able to detect it. Notice that, the primary and interference signal may follow any distribution, since we do not make any assumption about it. In this paper, we consider a distributed configuration where SU do not communicate with each other and only report their local sensing to a central processor known as fusion center (FC) [2], where according to a fusion rule a final decision is taken, and ultimately this decision is broadcast to all cooperating CR users. A particular scenario where the described assumptions can be applied is depicted in Fig.1, where a small cell (shadow one) within a heterogeneous network receives interference from neighbor cells during the time that the channel is considered quiet.

III. Kernel Canonical Correlation Analysis for CSS

Under the described assumptions, a local test problem at each SU given by $p_i(r_i|\mathcal{H}_1)/p_i(r_i|\mathcal{H}_0)$ is addressed by our KCCA scheme. It correctly provides the channel availability under interference by exploiting the correlation among the received signals at the FC. For this purpose, the energy of the received signal is employed which allow us to make no assumptions about the primary signal. We denote x_{in}, as the energy of the received signal r_i calculated over N_s samples during the n-th sensing period. In the following subsections, we briefly describes our KCCA scheme that consists of a learning stage, after which a detector is obtained and applied for online detection.

Learning Stage

During this stage, a set of data composed of N values, that is $\{x_{i1}, x_{i2}, ...x_{iN}\}$, is collected at the FC and for each i-th SU. KCCA allow us to find the transformation of these set of data with the maximal correlation, and non-Linear transformations will take them from its input space to a high-dimensional space $x_{in} \to \Phi(x_{in})$, where it is more likely that the problem can be solved in a linear manner. This is calculated without the explicit knowledge of the non-linear transformation $\Phi(x_{in})$ by employing a kernel function on pairs of data points in the input space whose corresponding Gram matrices $\mathbf{K}_i$ (or "kernel" matrices) can be calculated as,

$$\mathbf{K}_i(\ _j,\ _k) = \Phi_i(x_{ij})^\top \Phi_i(x_{ik}) = \kappa_i(x_{ij}, x_{ik}), \tag{1}$$

In short, KCCA provides the projections of the transformed data sets, $\mathbf{z}_i = \mathbf{K}_i\boldsymbol{\alpha}_i$, that have maximal correlation [13]. For reasons of simplicity, we consider an scenario with $M = 2$ SUs. Thus, the canonical correlation between the transformed data sets corresponding to a maximum variance (MAXVAR) formulation, is given by $\rho = \mathbf{z}_1^\top \mathbf{z}_2 = \boldsymbol{\alpha}_1^\top \mathbf{K}_1\mathbf{K}_2\boldsymbol{\alpha}_2$. The solution of the KCCA problem can be found by solving the following generalized eigenvalue problem (GEV) [13].

$$\frac{1}{M}\mathbf{R}\boldsymbol{\alpha} = \beta\mathbf{D}\boldsymbol{\alpha}, \tag{2}$$

where $\mathbf{R}$, is defined as,

$$\mathbf{R} = \begin{bmatrix} \mathbf{K}_1\mathbf{K}_1 & \mathbf{K}_1\mathbf{K}_2 \\ \mathbf{K}_2\mathbf{K}_1 & \mathbf{K}_2\mathbf{K}_2 \end{bmatrix} \tag{3}$$

and $\mathbf{D}$ as,

$$\mathbf{D} = \begin{bmatrix} \mathbf{K}_1(\mathbf{K}_1 + c\mathbf{I}) & \mathbf{0} \\ \mathbf{0} & \mathbf{K}_2(\mathbf{K}_2 + c\mathbf{I}) \end{bmatrix}. \tag{4}$$

In this case $\boldsymbol{\alpha} = [\boldsymbol{\alpha}_1^\top, \boldsymbol{\alpha}_2^\top]^\top$ and $\beta = \frac{1+\rho}{2}$, the canonical weights $\boldsymbol{\alpha}_i$ are retrieved as the eigenvector corresponding to the largest eigenvalue of the GEV problem (2). For a more detailed description, the reader may refer to [12], and references therein.

KCCA Detector

After a learning stage where the canonical weights are obtained, our detector is given by the projection of the transformed data,

$$T_i(x_{in}) = \sum_{j=1}^{N} \alpha_{ij}\kappa_i(x_{in}, x_{ij})$$

where α_{ij} refers to the j-th element of the canonical vector $\boldsymbol{\alpha}_i$. Notice that κ_i utilizes both the training data set and the energy level x_{in} over which it will make a decision.

IV. Testbed Description

A cognitive radio platform has been built by integrating USRP devices. Each of these nodes work with a universal hardware driver (UHD) as a host driver which includes a set of Application Programming Interface (API) functions. We have developed our own Universal Software Architecture for Software Defined Radio (USASDR), this third-party application employs the set of API function, by including them into higher level instructions from Matlab. In addition, it allow us to control simultaneously several USRP nodes, by means of a unique controller identified by an IP address that receives instructions from a remote PC. Both the transmitters and the receivers are composed of N210 USRP nodes, and the Radio Frequency (RF) part is equipped with a XCVR2450 daughterboard, which allows us to operate in the industrial, scientific, and medical (ISM) band of 4.9GHz to 5.9GHz, thus avoiding any device transmitting in the same band, a more

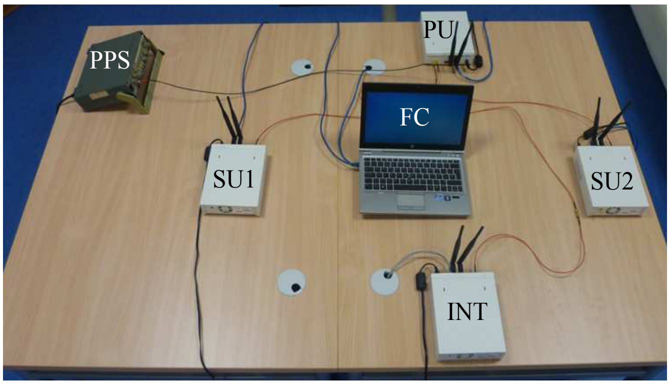


Fig. 2. Two SU as sensing nodes, an interfering node (INT), a PU, and a FC in the middle of them. All USRP are synchronized by a pulse per second signal (PPS) provided by Signal Generator.

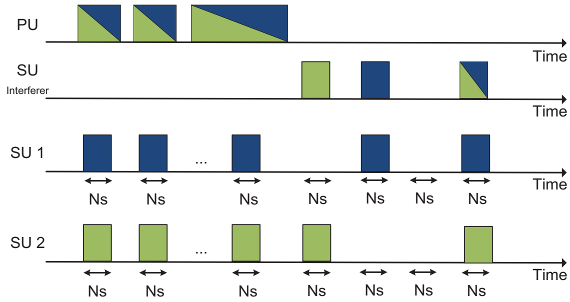


Fig. 3. Measurement procedure: the PU transmits using two bands of frequency channels represented by two colors (2–4MHz & 4–6MHz), whereas a SU (interferering node) transmits randomly on any of these bands, and the other SUs sense one of these bands of frequency.

detailed description of these devices can be found in [10], [14]. We employ four USRP nodes for the considered scenario, as it is shown in Fig. 2, where a PU, two SU nodes and an interfering node are configured and synchronized in time by a pulse per second (PPS) signal for simultaneous transmission and reception during the measurement procedure.

A. Measurement Procedure

All the measurements were tested in an indoor channel at 5.6 GHz. Under this stationary environment, two SU will start sensing simultaneously the wireless channel while being randomly interfered by the interfering node. With this aim, we emulate interference to each SU independently by allowing the interfering node to randomly transmit on two different channels of frequency, that is, 2–4MHz and 4–6MHz. Each of these bands of frequency is only sensed by a SU, and the PU transmit a signal whose bandwidth covers both bands of frequency (2–6MHz). In this configuration, both SUs, only one of them, or neither of them will be affected by the interference, while both of them are able to detect a busy channel when the PU is present. The transmission/sensing cycle is shown in Fig. 3, where the transmitted signal is an orthogonal frequency division multiplexing (OFDM) waveform, that follows the standard IEEE 802.11a. This waveform is generated with a rate of 9 Mbps using BPKS symbols, and up-sampled to modify the bandwidth of the signal so as to accomplish the described configuration. After sensing several times, a set of data $\{x_{i1}, x_{i2}, ...x_{iN}\}$, composed of the estimated energy levels are collected in a central PC acting as a FC. After which the canonical weights $\boldsymbol{\alpha}_i$ are calculated and included in the statistic T_i whose performance is evaluated during an offline process.

V. Experimental Results

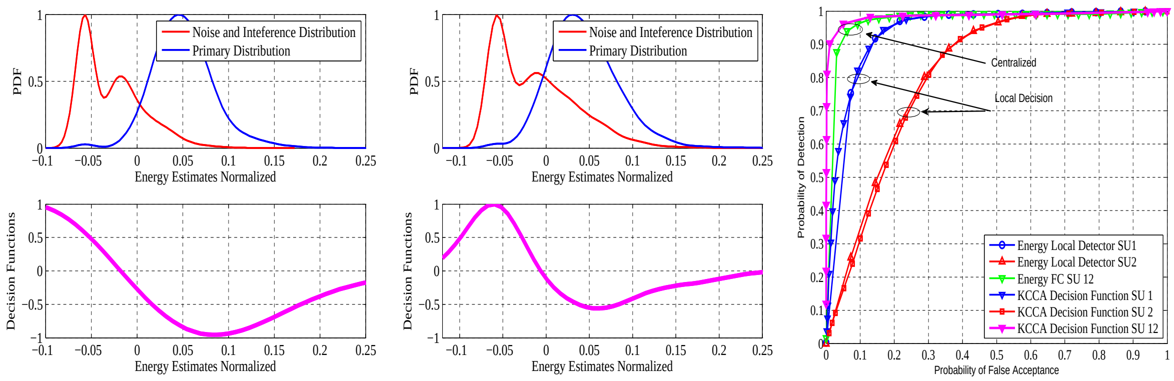
In this section, we describe the results obtained by the mentioned procedure, and highlight more challenging cases where the interference is present during the sensing period. The following results were obtained for $M = 2$, $N_s = 50$, and $N = 300$. For the KCCA detector, a Gaussian kernel function of the form $k_i(x_{in}, x_{im}) = \exp(-(x_{in} - x_{jn})^2/2w^2)$ is selected and the kernel width w is fixed according to a Silverman's rule [15]. We study the decision functions given by T_i, and its detection performance by showing the Receiving Operating Characteristic (ROC) curves.

A. Decision functions for KCCA

In Figs. 4(a) and 4(b) the probability density function (PDF) of the measured energy levels are shown for each SU under both hypothesis, and these curves are superimposed over the decision function T_i. It can be observed that the primary, the noise and the interfering signal follow chi-square distributions, and the decision function (the projection of the transformed data set) obtained by KCCA is able to separate them by assigning negative values to the primary signal, whereas more positive values are assigned to the noise and interfering signal. A more interesting case is depicted in Figs. 5(a) and 5(b), for which a more non-linear decision functions are required to detect the primary signal placed between the noise and the interfering signal. Although, few lower and higher values are mapped around a zero value, the sensing performance is not severely degraded, and it can be attributed to the shape of the decision function composed of Gaussian functions.

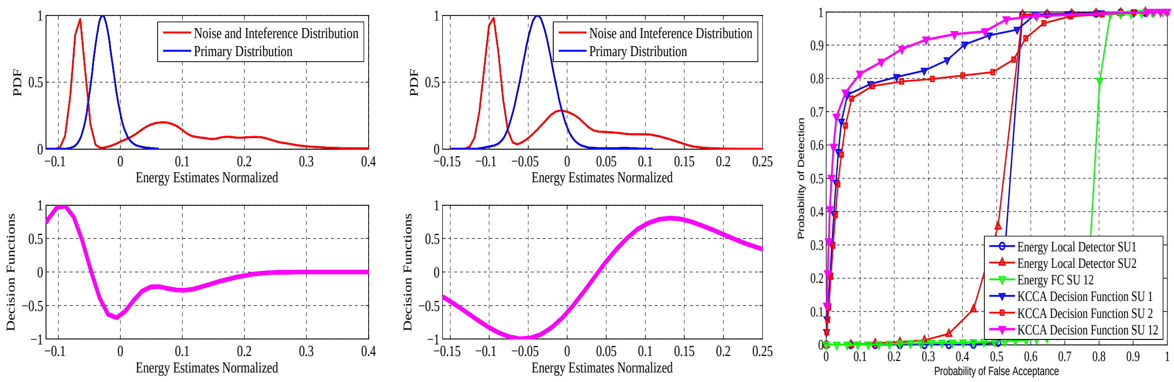
B. Receiver Operating Characteristics

The corresponding ROC curves for the described examples are depicted in Fig. 4(c), and Fig. 5(c) respectively. We compare the results obtained by a KCCA and an energy detector, for each SU and both SU. For our KCCA detector, the results at each local SU are obtained after exploiting the non-linear correlation among the received signal at the FC and broadcasting the obtained decision functions to each local SU. On the other hand, the performance results for both detectors at the FC are obtained by the sum of their statistics as a fusion rule. The Fig. 4(c) shows that the obtained performance of both detector are quite similar at each SU, whereas a slight gain is attained by the KCCA detector at the FC, which can be explained from the fact our proposal exploit information of correlation from the other SU during the learning stage. In Fig. 5(c), we observe that the energy detector is clearly outperformed by the KCCA detector since it is unable to



(a) (b) (c)

Fig. 4. Scenario 1: KCCA decision function and PDF for the primary, the interfering and noise signal. (a) at SU 1. (b) at SU 2, both of them with an estimated SINR ≈ 0.63 dB, (c) ROC Curves for the KCCA and energy detector.



(a) (b) (c)

Fig. 5. Scenario 2: KCCA decision function and PDF for the primary, the interfering and noise signal. (a) at SU 1 with an estimated SINR ≈ -6.32 dB, (b) at SU 2 with an estimated SINR ≈ -5.12 dB (c) ROC Curves for the KCCA and energy detector.

distinguish between the primary signal and the impairments, whereas the interference diversity is exploited by our proposal to obtain a considerable advantage.

VI. Conclusions

In this paper we have experimentally evaluated a KCCA detector for a CSS problem where not only noise, but also interference is considered. Our proposal blindly learns during a learning stage the required decision functions to correctly detect the primary signal, and the experimental results shows that under interference our KCCA detector obtains a considerable gain over an energy detector.

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