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

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***Abstract*—The cognitive radio (CR) paradigm relies on accurate spectrum sensing schemes. These schemes can benefit from spatial or multiuser diversity, though they need to be able to work under non-ideal scenarios, such as those affected by impairments or interferences. In this paper, a cooperative spectrum sensing (CSS) technique is experimentally evaluated by means of a CR testbed. The proposed method is based on kernel canonical correlation analysis (KCCA), which is performed at the fusion center (FC) in a first cooperative stage. In particular, the FC extracts the local test statistics for the different sensors, without the need of any training signal or labeled data, after which the sensors can operate in a completely autonomous manner. 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 to learn the surrounding environment by exploiting only the nonlinear correlation among the signals at each secondary user (SU). Moreover, we illustrate the performance of the proposed technique in the presence of local interferers, where we can appreciate a significant performance gain over a conventional energy-based cooperative detector.**

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

I. Introduction

Cognitive Radio (CR) systems allow sharing the spectrum between primary users (PUs) and non-legacy users (secondary users or SUs). This technology relies on a spectrum sensing process for detecting exploitable holes in the spectrum, which can be filled by subsequent SU transmissions.

In order to improve the performance of spectrum sensing techniques, multiantenna and cooperative approaches have been previously considered [1]. However, the need for robust methods able to operate under the presence of interferers [2], [3] and/or non-Gaussian noise [4], makes the design of practical spectrum sensing approaches a challenging problem.

In this paper, we evaluate a recently proposed spectrum sensing technique [5] by means of experimental measurements using a CR testbed. The proposed method aims to extract, in a completely unsupervised manner, the local decision rules to be used at different sensors or SUs, and it is solely based on the assumption of conditionally independent measures under the null hypothesis (absence of PU). Specifically, in a first cooperative stage, the different sensors transmit the estimated energy measured over a sensing period to a FC, which retrieves the non-linear transformations providing maximum correlation by means of kernel canonical correlation analysis (KCCA). The nonlinearly transformed observations will be used as local test statistics at the sensors, which can then operate in a completely autonomous manner.

Despite the vast amount of spectrum sensing techniques proposed in the literature, only a few of them have been evaluated by means of experimental measurements [6]–[9]. In this paper, we evaluate the performance of the proposed spectrum sensing approach, taking into account the possible presence of an external interferer. The experiments are conducted in a hardware platform consisting of several USRP nodes. The results show that the proposed approach is robust to interferers, providing either local (at the SU) or global (at the FC) reliable decisions.

II. Cooperative Spectrum Sensing

Let us consider a scenario with M secondary users, in which local interferences are (possibly) present under the null hypothesis. The signal model can be written as

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

where r_i denotes the received signal at the i-th SU, $\mathbf{r}$ is a vector signal composed of all observations, $\mathcal{H}_1$ denotes the alternative hypothesis (PU active) and $\mathcal{H}_0$ is the null hypothesis (idle channel). That is, our signal model solely relies on the assumption that the sensor measurements are conditionally independent under $\mathcal{H}_0$, but not under $\mathcal{H}_1$. Thus, the proposed model considers a very general scenario in which the SUs might be affected by local and thus independent interferences. Note also that the primary, interference and noise signals can follow any distribution, since we do not make any assumption (apart from independence when the channel is idle) about them. A particular scenario where the described assumptions hold is depicted in Fig.1, where a small cell (shadowed) within a heterogeneous network (HetNet) receives interference from neighboring cells during the time that the channel is considered vacant.

In the considered model, there is an initial cooperative stage in which all secondary users report their unlabeled energy

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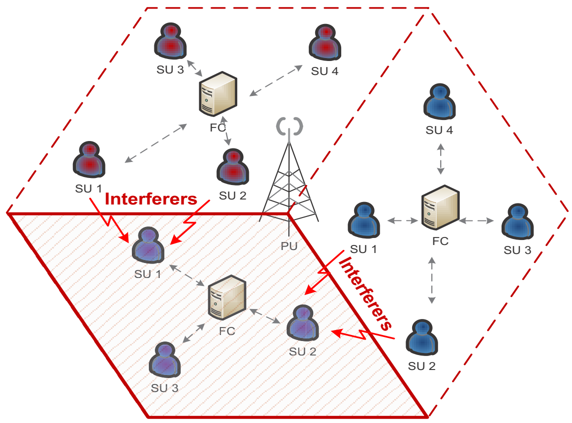


Fig. 1. A spectrum sensing problem in a HetNet. Three SUs in a small cell cooperate to detect the presence of a PU, while two of them receive interference from other small cells. The interferences are independent of each other.

measurements to a fusion center (FC) via orthogonal channels [1]. The FC then exploits the statistical dependencies among the SU measurements to obtain the local test statistics. Once each SU knows its local statistic, the network is able to operate in a distributed manner, with each SU taking its own decisions. Nevertheless, a centralized version in which the SUs report their statistics to the FC, which then takes the final decision, is also possible.

III. Cooperative Sensing via KCCA

The problem to be solved consists in finding test statistics at each SU with the only assumption that they should be conditionally independent under $\mathcal{H}_0$, but not under $\mathcal{H}_1$. To solve this problem we exploit the fact that the local test statistics should be approximately those non-linear transformations of the input data that maximize the correlation among sensors. To find these nonlinear transformations we apply kernel canonical correlation analysis (KCCA) [5]. In this paper, as input data of the KCCA approach we exclusively focus on the energy of the received signals,[1] and denote x_{in} as the energy of the received signal r_i estimated over N_s samples during the n-th sensing period.

Initial Cooperative Stage

During the first cooperative stage, M sets of data, each one composed of N values (that is, for the i-th SU we have $\{x_{i1}, x_{i2}, ...x_{iN}\}$), are collected at the FC. The local test statistics are then obtained at the FC by means of KCCA. This kernel-based method obtains the sought non-linear transformations as linear projections in a high dimensional (feature) space ($x_{in} \rightarrow \Phi(x_{in})$), where inner products can be calculated without the explicit knowledge of the mapping $\Phi(x_{in})$ by employing a kernel function $\kappa(\cdot,\cdot)$ on pairs of data points in the input space. Specifically, the Gram (or "kernel") matrices for each dataset $\mathbf{K}_i$ are defined as

$$\mathbf{K}_i(j,k) = \Phi(x_{ij})^\top \Phi(x_{ik}) = \kappa(x_{ij}, x_{ik}), \tag{1}$$

In short, KCCA provides the projections of the transformed data sets, $\mathbf{z}_i = \mathbf{K}_i \boldsymbol{\alpha}_i$, with maximal correlation [10]. For reasons of simplicity, we consider a scenario with $M = 2$ SUs. Thus, the canonical correlation between the transformed data sets 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) [10].

$$\begin{bmatrix} \mathbf{K}_1\mathbf{K}_1 & \mathbf{K}_1\mathbf{K}_2 \\ \mathbf{K}_2\mathbf{K}_1 & \mathbf{K}_2\mathbf{K}_2 \end{bmatrix} \boldsymbol{\alpha} = \beta \begin{bmatrix} \mathbf{K}_1(\mathbf{K}_1 + c\mathbf{I}) & \mathbf{0} \\ \mathbf{0} & \mathbf{K}_2(\mathbf{K}_2 + c\mathbf{I}) \end{bmatrix} \boldsymbol{\alpha}, \tag{2}$$

where $\beta = 1 + \rho$, c is a regularization constant, $\boldsymbol{\alpha} = [\boldsymbol{\alpha}_1^\top, \boldsymbol{\alpha}_2^\top]^\top$, and 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 [5] and references therein.

KCCA Local and Global Tests

After the training stage, the local detectors at each SU are given by the obtained non-linear transformations, which can be easily computed as

$$T_i(x) = \sum_{j=1}^{N} \alpha_{ij} \kappa(x, x_{ij}) \tag{3}$$

where α_{ij} refers to the j-th element of the canonical vector $\boldsymbol{\alpha}_i$. Notice that $\kappa(x, x_{ij})$ measures the similarity between the new energy measurement, x, and the training data set for the i-th SU. The final statistic is a weighted sum of these similarities. Once the SUs compute their test statistics, local decisions reduce to a comparison of (3) with a threshold. However, if the communication with the FC is affordable, the local tests can be combined in the FC by simply adding the test statistics.[2]

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), which allows us to control several USRP nodes simultaneously 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 USRP N210 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. A more detailed description of these devices can be found in [9], [11]. Our CR testbed uses four USRP nodes as shown in Fig. 2, where a PU, two SU

[1]Other choices are obviously possible, ranging from the processing of the whole raw dataset, r_i, to processing only a vector of extracted features (energy, kurtosis, etc.). In practice, we can expect a tradeoff among performance, number of features, and temporal coherence of the channels.

[2]This procedure is not simply a heuristic rule, but it represents the best one-dimensional representation of the maximally correlated non-linear transformations.

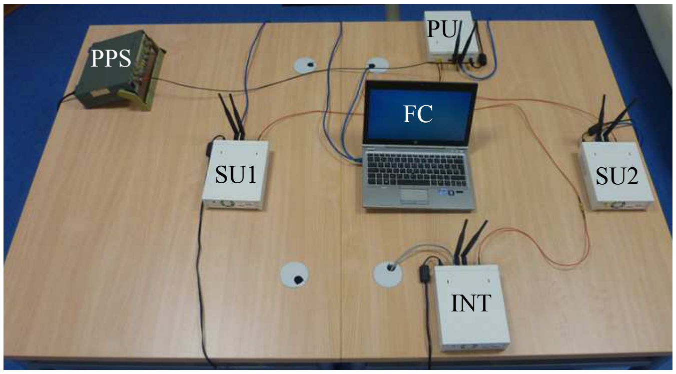


Fig. 2. Two SUs as sensing nodes, an interfering node (INT), a PU, and a FC in the middle of them. All USRP are synchronized by a pulse per second signal (PPS) provided by Signal Generator. The SUs are located at approximately 1 m from the PU and the interfering node.

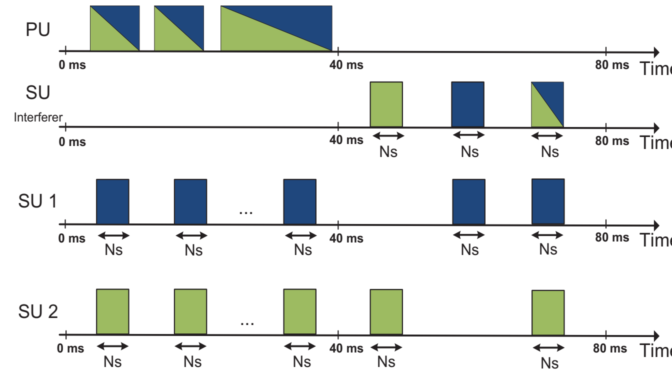


Fig. 3. Measurement procedure: the PU transmits over the two sub-channels represented by two colors, each SU senses a different band, and the interfering node transmits randomly on any of the channels, or in both.

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 quasi-static (the coherence time is rather long in comparison to the measurement time) channel of 4 MHz centered at 5.6 GHz. To recreate a scenario in which the interferences observed by each SU are independent, we divide the 4 MHz channel into 2 sub-channels of 2 MHz each. Each SU senses a different sub-channel, whereas the PU transmits over the whole 4 MHz channel. On the other hand, the interfering node randomly transmits on one of the two sub-channels, or on both simultaneously following independent Bernoulli distributions with a probability of sub-channel occupancy $p = 0.5$. In this configuration, either both SUs, only one of them, or neither of them will be affected by the interference, while both SUs 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 IEEE 802.11a standard. This waveform is generated with a rate of 9 Mbps using BPSK symbols, and resampled with a rational factor to modify the bandwidth of the signal so as to accomplish the described configuration. After multiple sensing periods, two sets of data composed of the estimated energy levels [3] at each SU, are collected in a central PC acting as a FC. Finally, the canonical weights $\boldsymbol{\alpha}_i$ are calculated and used to form the statistic $T_i(x)$, whose performance is evaluated during an off-line process.

V. Experimental Results

In this section, we describe the obtained results and highlight the more challenging cases where the interference is present during the sensing period. The following results were

[3] Energy levels are measured in this work as the energy of the discrete-time signal normalized by the maximum value found among all measurements.

obtained for $M = 2$, $N_s = 50$, and $N = 300$. [4] For the KCCA detector, a Gaussian kernel function of the form $k(x_i, x_j) = \exp(-(x_i - x_j)^2/2w^2)$ is selected, the kernel width w is fixed according to the Silverman's rule [12], and the regularization parameter in (2) is set to $c = 10$. We study the decision functions, T_i, and their detection performance by showing the Receiving Operating Characteristic (ROC) curves.

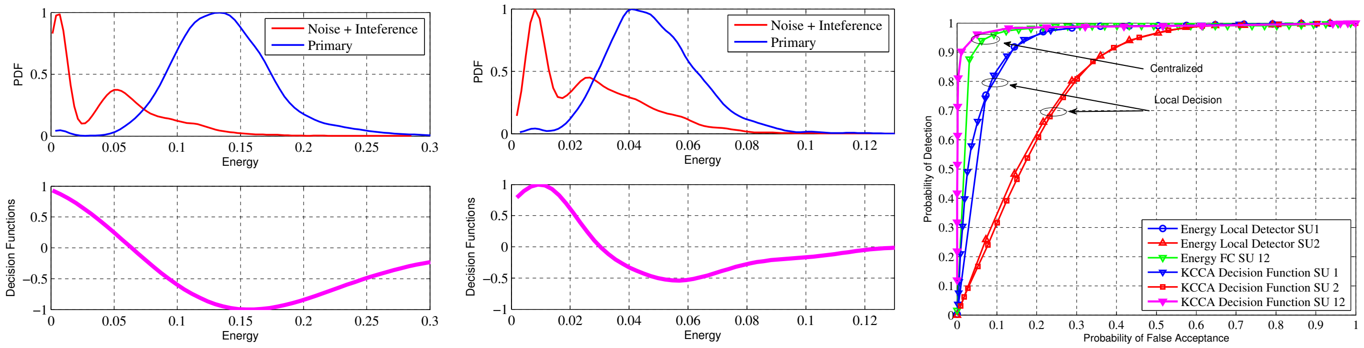
A. *Decision functions for KCCA*

In Figs. 4(a) and 4(b) the probability density function (PDF) of the measured energy levels is shown for each SU under both hypothesis, as well as the decision function T_i. The signal-to-interference-plus-noise-ratio (SINR) for both SUs is approximately 0.6 dB. It can be observed that the KCCA decision function is able to separate the two hypotheses by assigning small values to the primary signal and larger values to the interference-plus-noise signal. A more interesting case is depicted in Figs. 5(a) and 5(b), where the detection of the primary, whose energy takes values between those of the noise and the interference, requires strongly non-linear decision functions. In this example, the SINR at SU 1 and SU 2 are -6.3 dB and -5.1 dB, respectively.

B. *Receiver Operating Characteristics*

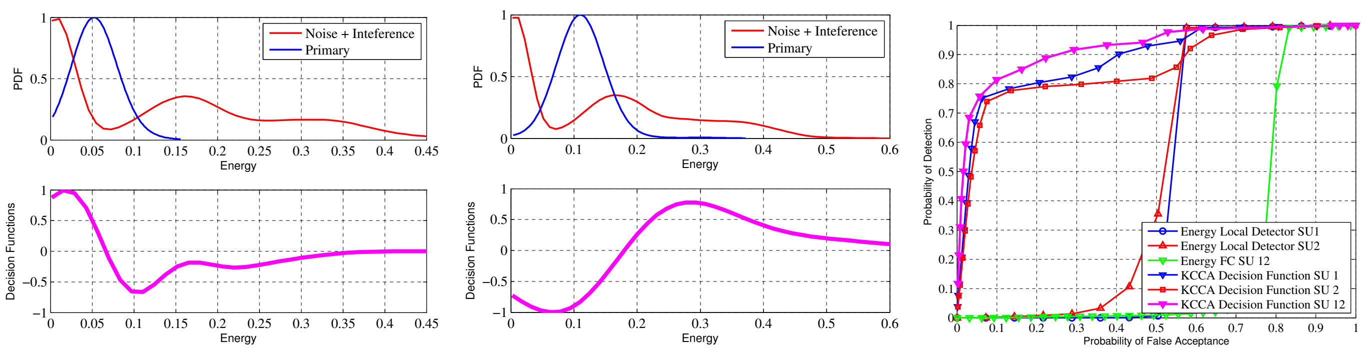
The corresponding ROC curves for the described examples are depicted in Figs. 4(c) and 5(c), respectively. We compare the results obtained by KCCA and a conventional energy detector, both for local (at each SU) and global (at the FC) decisions. In particular, the results for both detectors at the FC are obtained by adding the local test statistics as a fusion rule. Fig. 4(c) shows that the obtained performance of both local detectors are similar, whereas a slight gain is attained by the KCCA detector at the FC. In Fig. 5(c), we observe that the proposed KCCA method clearly outperforms the energy

[4] During the learning stage it is assumed that the channel remains constant. On the other hand, during the operational stage the pdfs under both hypotheses should not change, otherwise the KCCA-based detector would fail unless some updating procedure is implemented. The maximum transmission power is set to 5 dBm, and it is attenuated by applying a constant factor to the signal's amplitude.



(a) (b) (c)

Fig. 4. Scenario 1: KCCA decision function and PDF for the primary and the interference-plus-noise signal. (a) at SU 1. (b) at SU 2, both of them with an estimated SINR ≈ 0.6 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 and the interference-plus-noise signal. (a) at SU 1 with an estimated SINR ≈ -6.3 dB, (b) at SU 2 with an estimated SINR ≈ -5.1 dB (c) ROC curves for the KCCA and energy detector.

detector, which is unable to distinguish between the primary and interference signals.

VI. Conclusions

This paper has illustrated the performance of a KCCA-based spectrum sensing technique, by means of over-the-air experiments in a hardware testbed. During a first cooperative stage, the proposed technique extracts the local test statistics to be used at each SU, which can then operate in a completely autonomous manner. The obtained results show that the proposed method is robust to interferences, and it clearly outperforms the energy detector in these scenarios.

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