When Machine Learning Meets Compressive Sampling for Wideband Spectrum Sensing

Bassem Khalfi, Adem Zaid, Bechir Hamdaoui
Oregon State University, Oregon, USA
{khalfib,zaida,hamdaoui}@oregonstate.edu

***Abstract*—This paper proposes a novel technique that exploits spectrum occupancy behaviors inherent to wideband spectrum access to enable efficient cooperative wideband spectrum sensing. Our technique requires lesser number of sensing measurements while still recovering spectrum occupancy information accurately. It does so by leveraging compressive sampling theory to exploit the block-like occupancy structure of wideband spectrum access. Our technique is also adaptive in that it accounts for the variability of spectrum occupancy over time. It exploits supervised learning to provide and use accurate realtime estimates of the spectrum occupancy. Using simulations, we show that our proposed technique outperforms existing approaches by making accurate spectrum occupancy decisions with lesser sensing communication and energy overheads.**

***Index Terms*—Cooperative wideband spectrum sensing; compressive sampling; supervised learning.**

I. Introduction

Spectrum availability presents a major challenge that fifth-generation (5G) networks need to overcome in order to support the massive number of emerging 5G devices. In an effort to overcome this foreseen challenge, spectrum regulators have started to create service rules and policies for allowing high frequency band use. For example, as recently as July 2016, FCC established new rules for opening up mmWave band use for wireless broadband devices in frequencies above 24 GHz [1]. With these new rules, 5G networks will be forced to operate in a wide range of spectrum bands with diverse characteristics and limitations (e.g. propagation condition, transmission power limits, etc.). These new spectrum access policies call for innovative techniques that enable the access of this wideband spectrum in an efficient manner.

On the other hand, despite the rapidly increasing number of users, recent measurement studies [2] reveal that the allocated spectrum still suffers from under-utilization. As a result, dynamic spectrum access (DSA) has been adopted by 5G as the key solution for addressing this spectrum access inefficiency [3]–[7]. The core idea of DSA is to rely on spectrum sensing techniques to locate unoccupied bands that can be exploited opportunistically by secondary users (SUs) [8]–[14].

Many techniques have already been proposed with the aim of improving spectrum sensing, but mostly for single-band DSA [15]–[18]. Wideband spectrum sensing has, however, received lesser attention [19]. Most of wideband spectrum sensing techniques leverage compressive sampling theory [20] to exploit the inherent sparsity nature of wideband occupancy, thus allowing for spectrum occupancy information recovery at sub-Nyquiest sampling rates. Applying compressive sampling requires the estimation of the sparsity level which reflects the spectrum occupancy [20]. In the literature, this sparsity level has usually been set to the average occupancy across the entire wideband spectrum [19], [21]. However, spectrum occupancy is a time-varying process, and hence, setting it to a fixed average makes these compressive sampling based techniques inefficient. More specifically, when the actual sparsity level is higher than this used average, compressive spectrum sensing techniques fail to recover the spectrum occupancy information, and when it is below the average, SUs end up taking more measurements than needed, which leads to wasting energy and bandwidth resources.

In this paper, we propose a novel technique that enables efficient cooperative spectrum sensing in wideband DSA. The novelty of our proposed technique lies in the key observations that spectrum occupancy (i) changes over time and (ii) varies considerably from one spectrum block to another [2]. Our technique accounts for the time variability by leveraging supervised learning [22] to provide and use estimates of the sparsity levels, and exploits the block-like spectrum occupancy structure by leveraging compressive sampling [20] to reduce the number of measurements needed to recover spectrum occupancy information. Our technique tracks and provides a sparsity level estimate in realtime for each spectrum block separately to exploit the observed block-like occupancy behavior and to account for time variability of these occupancies. The tracking and incorporation of this adaptive, fine-grained spectrum occupancy is the key behind the performance improvement that our proposed technique achieves. To this end, our contributions in this paper are:

- We propose an efficient spectrum sensing technique for cooperative wideband spectrum access that overcomes the shortcomings of conventional approaches. It combines machine learning with weighted compressive sampling to accurately estimate wideband spectrum occupancy.
- We propose prediction approaches that rely on regression to provide accurate estimates of the sparsity levels, thereby allowing efficient spectrum occupancy information recovery.
- We propose a weighted compressive sampling approach that exploits the block-like, inherent structure of spectrum occupancy to enable efficient recovery of wideband occupancy information.

The remainder of the paper is structured as follows. In Section II, we present our system model. In Section III, we describe our proposed scheme. In Section IV, we present the performance evaluation of the proposed technique. Related works are presented in Section V. Finally, we present our conclusion and future works in Section VI.

II. System Model

A. Primary System Model

We consider a heterogeneous wideband spectrum access system containing n frequency bands. We assume that wideband spectrum accommodates multiple types of user applications, where applications of the same type are allocated frequency bands within the same block. Therefore, we consider that wideband spectrum has a block-like occupation structure, where each block (accommodating applications of similar type) has different occupancy behavioral characteristics (as observed in [2]). The wideband spectrum can then be grouped into g disjoint contiguous blocks, $\mathcal{G}_i, i = 1, ..., g$, with $\mathcal{G}_i \bigcap \mathcal{G}_j = \emptyset$ for $i \neq j$. Each block, $\mathcal{G}_i$, is a set of n_i contiguous bands. We assume that within each block $\mathcal{G}_i$ of frequency, the number of primary users (PU)s' arrivals within a time slot T and the service time/duration of each PU, each follows some probabilistic distribution. Therefore, our system can be seen as g $G/G/n_i/n_i$ independent queueing systems.

B. Secondary System Model

We consider a set of SUs co-located in the same cell as the PUs, and assume that a subset of SUs perform the wideband spectrum sensing task cooperatively, as illustrated by Fig. 1, and report their sensing measurements to a fusion center (FC), which uses them to determine whether the spectrum is occupied. The FC then relies on this spectrum occupancy information to assign spectrum to the SUs requesting spectrum access. Further details on the cooperative sensing protocol are given in Section III.

The time-domain signal $\boldsymbol{r}_i(t)$ received by the ith SU can be expressed as

$$\boldsymbol{r}_i(t) = \boldsymbol{h}_i(t) \otimes \boldsymbol{s}(t) + \boldsymbol{w}_i(t), \tag{1}$$

where $\boldsymbol{h}_i(t)$ is the channel impulse between the primary transmitters and the SU_i, $\boldsymbol{s}(t)$ is the PUs' signal, $\otimes$ stands for the convolution operator, and $\boldsymbol{w}_i(t)$ is an additive white Gaussian noise with mean 0 and variance σ^2. Ideally, the SU should take samples at a rate of at least twice the maximum frequency, $f_{\max}$, of the signal in order to ensure complete signal recovery. Let the sensing window be $[0, mT_0]$ with $T_0 = 1/(2f_{\max})$. Assuming a normalized number of wideband Nyquist samples per band, then the vector of the taken samples is $\boldsymbol{r}_i(t) = [r_i(0), ..., r_i((m_0 - 1)T_0)]^T$ where $r_i(j) = r_i(t)|_{t=jT_0}$, for $j = 0, ..., m_0$, and $m_0 = n$. Note that a reasonable assumption that we make is that the sensing window length is assumed to be sufficiently small when compared to the time it takes a band state to change. That is, each band's occupancy is assumed to remain constant during each sensing time window.

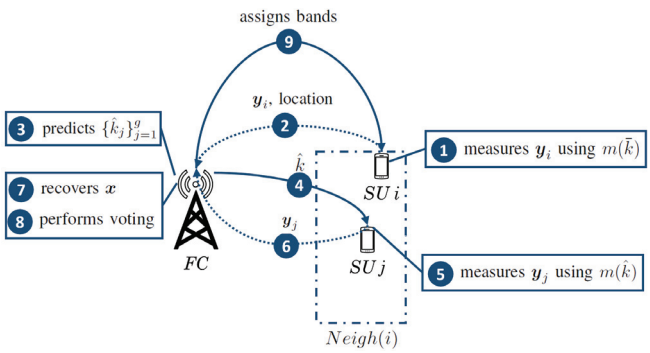


Fig. 1: Illustration of the cooperative spectrum sensing task.

To reveal which bands are occupied, the SU performs a discrete Fourier transform of the received signal $\boldsymbol{r}_i(t)$; i.e.,

$$\boldsymbol{r}_{f,i} = \boldsymbol{h}_{f,i}\boldsymbol{s}_f + \boldsymbol{w}_{f,i} = \boldsymbol{x}_i + \boldsymbol{w}_{f,i}, \tag{2}$$

where $\boldsymbol{h}_{f,i}$, $\boldsymbol{s}_f$, and $\boldsymbol{w}_{f,i}$ are the Fourier transforms of $\boldsymbol{h}_i(t)$, $\boldsymbol{s}(t)$, and $\boldsymbol{w}_i(t)$, respectively. The vector $\boldsymbol{x}_i$ contains a faded version of the PUs' signals operating in the different bands. Given the occupancy of the bands by their PUs and in the absence of fading and interference, the vector $\boldsymbol{x}_i$ is *sparse*. Formally, a vector $\boldsymbol{x} \in \mathbb{R}^n$ is said *k-sparse* if it has (or after performing a basis change) at most k non-zero elements [20]. That is, $supp(\boldsymbol{x}) = \|\boldsymbol{x}\|_{\ell_0} = |\{i : x_i \neq 0\}| \leq k$. But since, in practice, there will likely be interference coming from other nearby cells and users, the vector $\boldsymbol{x}_i$ could rather be *nearly sparse* than sparse. Mathematically, a vector $\boldsymbol{x} \in \mathbb{R}^n$ is said *nearly sparse* (called also compressible [20]) if most of its components obey a fast power law decay.

Sampling the wideband signal at the Nyquist rate is prohibitively costly, and goes beyond the hardware capabilities of the SUs. Compressive sampling has been used to overcome this issue by reducing the number of measurements significantly given that the signal is nearly sparse [20]. Hence, the measured signal can be written as

$$\begin{aligned} \boldsymbol{y}_i &= \Psi\mathcal{F}^{-1}(\boldsymbol{x}_i + \boldsymbol{w}_{f,i}) \\ &= \mathcal{A}\boldsymbol{x}_i + \boldsymbol{\eta}, \end{aligned} \tag{3}$$

where $\boldsymbol{y}_i \in \mathbb{R}^m$ is the measurement vector, $\mathcal{F}^{-1}$ is the inverse discrete Fourier transform, and Ψ is the sensing matrix assumed to have a full rank, i.e. $rank(\Psi) = m$. The sensing noise $\boldsymbol{\eta}$ is equal to $\Psi\mathcal{F}^{-1}\boldsymbol{w}_f$. These measurements $\boldsymbol{y}_i$ are then sent to FC to perform the spectrum recovery and decide on the occupancy of each band in that given region.

III. The Proposed Cooperative Wideband Spectrum Sensing Scheme

In this section, we present our technique. We begin by describing the proposed sensing protocol. Then, we investigate the different approaches used for predicting the spectrum occupancy, and describe our prediction-based scheme proposed for enabling efficient spectrum occupancy information recovery.

A. The Proposed Scheme

Acquiring accurate and consistent spectrum occupancy information across the entire cell requires that all SUs perform wideband spectrum sensing and at every time slot. However, this is prohibitively costly, as it incurs excessive overhead (energy, communication, etc.), and is not efficient either, as not all SUs will be needing access to the spectrum. To address this, we therefore propose that the sensing task is performed only by and within the region whose SUs need spectrum access.

The proposed cooperative sensing scheme is described as shown in Fig. 1. First, we assume that FC computes over time the average occupancy $\bar{k}$ of the wideband spectrum and shares it with all SUs. Now, if a particular SU_i wants to access the spectrum, it takes $m(\bar{k})$ measurements such that $m(\bar{k}) = O(\bar{k}\log(n/\bar{k}))$ as described by Equation (3). Then, $SU\ i$ reports the measurement vector $\boldsymbol{y}_i$ and its location to FC. After receiving the measurements and exploiting the other features (as described later), FC predicts the actual sparsity level in each block $\{\hat{k}_j\}_{j=1}^{g}$, as will be explained in Section III-B. Then, FC communicates $\hat{k} = \sum_{j=1}^{g} \hat{k}_i$ to the recent neighbors of SU_i, denoted as $Neigh(i)$. Next, each SU of $Neigh(i)$ takes $m(\hat{k}) = \mathcal{O}(\hat{k}\log(n/\hat{k}))$ measurements. Then, these measurements are reported to FC which exploits the predicted sparsity levels to perform an efficient recovery, as explained in Section III-C. Having recovered the spectrum occupancy information, the energy level of each band is compared to a threshold λ, and then used to decide, using voting, on the band occupancy. This is summarized in Algorithm 1.

Algorithm 1 : Cooperative Wideband Spectrum Sensing

1: SU_i performs wideband spectrum sensing using $\bar{k}$.
2: SU_i reports $\boldsymbol{y}_i$ and its location to FC.
3: FC predicts $\{\hat{k}_j\}_{j=1}^{g}$.
4: FC multicasts $\hat{k}$ to $Neigh(i)$.
5: $Neigh(i)$ performs wideband spectrum sensing.
6: $Neigh(i)$ reports their measurements to FC.
7: FC recovers spectrum occupancy as seen by each SU.
8: FC uses voting to decide on the occupancy.
9: FC assigns some bands to SU i.

Using Step 2, FC uses the measurements $\boldsymbol{y}_i$ and the location to determine the features used to predict the sparsity levels in each block, $\{\hat{k}_j\}_{j=1}^{g}$. In Steps 4-5, the main intuition behind requesting the measurements only from the neighbors of SU_i is twofold. First, users which are near-by SU_i are most likely to observe the same occupancy of the spectrum, and therefore, combining the observations of $Neigh(i)$ would lead to a more accurate decision which is the benefit of the cooperation. Here, SUs which are far from SU_i are most likely to have a different observation of the spectrum occupancy, and hence, it is better to discard their contributions. Second, reducing the number of contributing SUs has a direct implication on reducing the total network overhead, as well as the sensing energy at these devices. In Step 7, the spectrum recovery is performed at FC since this entity has more computing capability and has no constraint on the energy consumption. In Step 8, any voting technique can still be applied once the spectrum decision is performed for every band. We use the majority voting [13].

Remark 1. During the sensing process initiated by SU_i, if one of $Neigh(i)$ requested to access the spectrum, FC does not need to re-initiate the sensing protocol. Spectrum bands are directly assigned to it from the set of available bands.

B. Spectrum Occupancy Prediction

Having accurate, realtime estimates of the spectrum occupancy sparsity level $k = \sum_{i=1}^{g} k_i$ is vital for determining the least number $m = O(k\log(n/k))$ of measurements required for compressive sampling to accurately recover the spectrum occupancy information [20]. In fact, because k varies with time, not having accurate values of k may lead to over- or under-sampling, which may in turn result in either inaccurate information recovery or unnecessary measurements. In this work, we investigated the use of regression models, a class of supervised learning algorithms, to derive prediction approaches that can provide accurate estimates of the occupancy level k_i for each block i. These regression models require havig historical data, referred to as training set, that connects the set of observed features with the occupancy level of each spectrum block. The training set consists of N training samples $\{(\boldsymbol{z}^{(j)}, \boldsymbol{k}^{(j)})\}_{j=1}^{N}$ where $\boldsymbol{z}$ represents the vector of features $\boldsymbol{z}^{(j)} = [z_1^{(j)}, .., z_d^{(j)}]$ and $\boldsymbol{k}^{(j)}$ is the block occupancy such that $\boldsymbol{k}^{(j)} = [k_1^{(j)}, .., k_g^{(j)}]$. For ease of presentation in this subsection, we drop the subscript i of the ith block from k_i as if the prediction is only for one block. Next, we present the used regression techniques, along with the features used for the prediction.

1) Proposed Features: We have used the following features.

- *PUs' activity statistics:* knowing some statistical information about previous PUs activities in the network can help FC predict future spectrum occupancy. This knowledge can for example be the average service time or inter-arrival rates of users that accessed the spectrum. It is worth mentioning here that we do not assume any prior knowledge of the PU distribution.
- *SUs' neighbors*: As mentioned earlier, we consider a cooperative scheme that takes advantage of neighboring idle SUs to perform accurate spectrum occupancy detection. Since FC uses voting when deciding about spectrum availability, the larger the number of neighboring SUs is, the more accurate the decision is [13].
- *Previous spectrum occupancy information:* with this feature, we are accounting for the change in the sparsity level between time slots t and $t-1$. The intuition behind this is that the sparsity level at time t is highly correlated (and is very likely to be close) to that at time $t-1$.
- *Current spectrum measurement:* This feature is correlated with the number of occupied bands. In fact, the number of measurements $m(\bar{k})$ contains a weighted version of the signals in the different bands.

2) Regression Techniques: Using these proposed features, we now investigate the use of the following regression models to design our prediction technique.

a) Linear regression using batch gradient descent: We model the spectrum occupancy of each block as $k = \boldsymbol{w}^T \boldsymbol{z} = \sum_{i=0}^{d} w_i z_i$ where $d = \lceil m(\bar{k}) \rceil + 4$ and the parameter $\boldsymbol{w}$ is searched using the batch gradient descent, which consists of adaptively determining $\boldsymbol{w} = [w_0, ..., w_d]^T$ that minimizes a loss function. We use as a loss function the mean square error defined as $\mathcal{J}(\boldsymbol{w}) = \frac{1}{2N} \sum_{i=1}^{N} \left(\boldsymbol{w}^T \boldsymbol{z}^{(i)} - k^{(i)}\right)^2$.

b) Support vector regression (SVR): The objective of SVR is to find the function $\boldsymbol{g}(\boldsymbol{z})$ that predicts k with at most ε error where $\boldsymbol{g}$ is defined as

$$\boldsymbol{g}(\boldsymbol{z}) = \langle \boldsymbol{w}, \boldsymbol{z} \rangle + b, b \in \mathbb{R}$$

where $\langle ., . \rangle$ represents the dot product and b represents the intercept [23]. Searching for the optimal $\boldsymbol{w}$ is the solution to the optimization problem that minimizes the error which looks for the hyperplane that maximizes the margin, with some error tolerance. It is formulated as

$$\begin{aligned} \min_{\boldsymbol{w}} \quad & \frac{1}{2}\|\boldsymbol{w}\|_2 + C \sum_{i=1}^{N} (\zeta_i + \zeta_i^*) \\ \text{s.t.} \quad & k^{(i)} - \boldsymbol{w}^T \boldsymbol{z}^{(i)} - b \leq \varepsilon + \zeta^i \\ & \boldsymbol{w}^T \boldsymbol{z}^{(i)} + b - k^{(i)} \leq \varepsilon + \zeta^{i*} \\ & \zeta^i, \zeta^{i*} \geq 0 \end{aligned}$$

The slack variables ζ^i and ζ^{i*} are introduced to tolerate some errors whenever the optimization is not feasible [23]. The first prediction technique that we use is linear SVR, which is defined as

$$k = \sum_{i=1}^{N} (\alpha^{(i)} - \alpha^{(i)^*}) \langle \boldsymbol{z}^{(i)}, \boldsymbol{z} \rangle + b$$

where $\alpha^{(i)}$ and $\alpha^{(i)^*}$ are the Lagrangian multipliers [23]. In general, when the data set is linearly inseparable, linear SVR may fail to achieve the optimal regression. Hence, kernel functions are used in this context to transform data set to high dimensional spaces to perform the linear separation [23]. In this case, non-linear SVR is written as

$$k = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) . \mathcal{K}(\boldsymbol{z}^{(i)}, \boldsymbol{z}) + b$$

where $\mathcal{K}(z^i, z^j) = \langle \phi(z^i) . \phi(z^j) \rangle$ and ϕ_i are mapping functions. In this work we used the Gaussian kernel function [23].

C. Spectrum Occupancy Information Recovery Approach

The proposed recovery scheme exploits the predicted estimates of the per-block spectrum occupancy to improve the recovery accuracy. We propose a weighted ℓ_1-minimization compressive sampling technique that favors the search in the unoccupied bands in the blocks with higher band occupancy.

Given the occupancy is different from one block to another, we propose to set the weights inversely proportional to the estimated block occupancy levels. Formally, the weights can be written as

$$\omega_i = \frac{1}{\hat{k}_i} / \sum_{j=1}^{g} \frac{1}{\hat{k}_j} \; \forall \, i = [1, ..., g] \tag{4}$$

and hence, our proposed recovery approach can be formulated as

$$\begin{aligned} \mathscr{P}(\boldsymbol{x}; \boldsymbol{\omega}) \quad \min_{x} \quad & \sum_{l=1}^{g} \omega_l \|\boldsymbol{x}_l\|_{\ell_1} \\ \text{s.t.} \quad & \|\mathcal{A}\boldsymbol{x} - \boldsymbol{y}\|_{\ell_2} \leq \epsilon. \end{aligned} \tag{5}$$

where $\boldsymbol{x} = [\boldsymbol{x}_1^T, ..., \boldsymbol{x}_g^T]^T$, $\boldsymbol{x}_l^T$ is a $n_l \times 1$ vector for $l \in \{1, ..., g\}$. The intuition behind this approach is to down-weigh the effect of the heavy-loaded blocks so that the search focuses on blocks with more unoccupied bands [24].

IV. Performance Evaluation

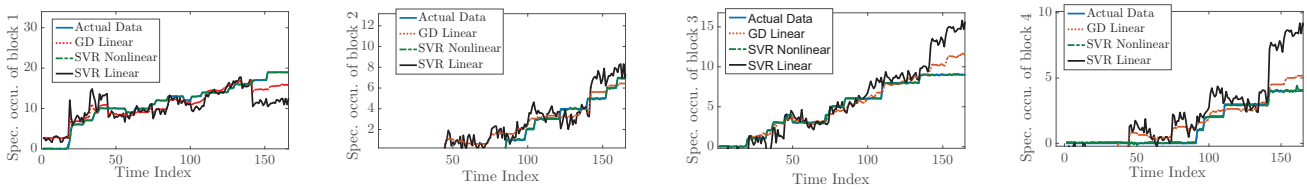
Our proposed technique is implemented using Matlab and python. We consider 500 SUs randomly deployed in a region of 1 km^2. The wireless transmission of SUs and PUs is mainly impacted by the path loss defined as $L_{dB} = 20\log(dist) + 20\log(f_i) - 27.55$ where $dist$ is the distance between the transmitting PU and the sensing SU and f_i is the carrier frequency over which users are operating. The used system parameters are summarized in Table I. FC stores the features defined in Section III-B1 as well as the occupancy of the blocks over a period of two hours resulting in more than 500 data samples. The 2/3 of resulted data set is served as the training set while 1/3 as a testing set. Then, we used scikit-learn package library in python [25] to implement the three regression models explained in Section III-B2.

TABLE I: System parameters.

System Parameters	
SU Transmit Power	33 dBm
PU Transmit Power	33 dBm
Coverage Area	1 km^2
Number of Channels n	256
Number of Blocks g	4
Decision Threshold λ	-100 dBm
Receiver Sensitivity	-100 dBm

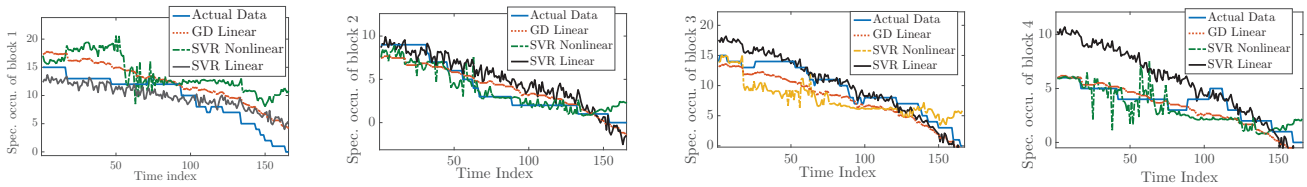
A. Evaluation of the Regression Techniques

Fig. 2a-2d show the predicted spectrum occupancy against the actual spectrum occupancy of each block using the training set. Observe that the models follow closely the behavior of the actual data which seems to have a random behavior across the different spectrum blocks. A second observation that we make is that the overall spectrum occupancy is sparse, time varying, and different from one block to another. Furthermore, we notice that the nonlinear SVR is the regression technique that achieves the best performance. Now, we assess the performance against the testing set as shown in Fig. 3a-3d. Overall, the regression techniques still follow the same behavior of the actual occupancy of every block. We observe that batch linear regression has a superior performance compared to the other



(a) Block 1. (b) Block 2. (c) Block 3. (d) Block 4.

Fig. 2: Performance of the regression techniques applied to the training data.



(a) Block 1. (b) Block 2. (c) Block 3. (d) Block 4.

Fig. 3: Performance of the regression techniques applied to the testing data.

in this case. We also observe that nonlinear SVR still behaves somehow better than the linear models. This is mainly because it gives more accurate support vectors and it deals better with data that is linearly inseparable.

B. Evaluation of the Proposed Sensing Scheme

Having assessed the performance of the prediction of the occupancy of every block, we look at the overall performance of our proposed scheme and the effectiveness of the recovery algorithm. We studied the false alarm and the miss-detection probabilities as measures of the effectiveness of our scheme. We compared the results against the traditional cooperative wideband spectrum sensing algorithm where measurements are taken based on the average spectrum occupancy $\bar{k}$. Here, a false alarm occurs when a band is declared occupied while it is not, whereas a miss-detection occurs when an occupied band is not detected. We take $m = 1.8k\log(n/k)$.

Fig. 4 shows the miss-detection performance achieved under our proposed technique using the three studied learning approaches, and compares it to that achieved under the conventional approach. We observe that gradient descent and linear SVR achieve superior performances when compared to that achieved under the nonlinear SVR. Surprisingly compared to the previous results, linear regressions achieve better performance. This is because these techniques over-predict the sparsity levels, and hence results in more taken measurements that help achieve better accuracy. Similar conclusions can be drawn with the false alarm results shown in Fig. 5.

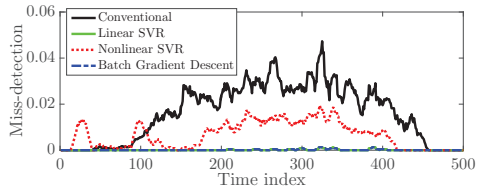


Fig. 4: Miss-detection performance evaluation of the proposed scheme under the different studied regression techniques compared to conventional approach [19].

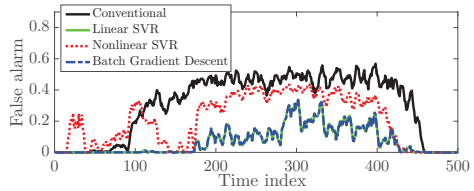


Fig. 5: False alarm performance evaluation of the proposed scheme under the different studied regression techniques compared to conventional approach [19].

V. Related Works

The application of machine learning techniques in the context of cognitive radio networks is not new [22], [26], [27]. Authors in [26] surveyed the use of machine learning in spectrum sensing. Authors in [22] have discussed the use of unsupervised and supervised learning techniques for cooperative spectrum sensing. The vector of energy is treated as the feature vector to be fed to the classifier. Although a good number of techniques has been tested, the main shortcoming of this work is that it is designed for single band spectrum sensing. Similar approaches using k-means and SVM are considered in [28]. Authors in [27] considered the case of multiband spectrum where the features are the status of the bands while authors in [29] used a multi-class support vector machine for cooperative wideband spectrum sensing. However, these approaches did not account for the heterogeneity of spectrum allocation nor did they consider wideband spectrum sensing. On the other hand, compressive sampling received

recently more research attention for cooperative wideband spectrum [19], [21]. Nevertheless, these works did not exploit the additional knowledge about the spectrum although there has been some works that aimed on exploiting additional knowledge about the signal in general frameworks but not in spectrum sampling [30]–[33]. This work aims at leveraging regression models to improve the performance of the cooperative sensing task while not incurring excessive energy and communication overheads.

VI. Conclusion

We proposed an efficient cooperative wideband spectrum technique that exploits regression techniques as well compressive sampling to improve the sensing performance. We applied supervised learning to provide accurate estimates of the wideband spectrum occupancy, and compressive sampling theory to reduce the number of needed sensing measurements. We proposed an efficient spectrum occupancy information recovery scheme, and showed that our scheme makes great performance enhancements in terms of sensing overhead, sensing energy, and spectrum decision accuracy.

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