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

Leveraging Compressive Sampling and Machine Learning for Adaptive and Cooperative Wideband Spectrum Sensing

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Adem Zaid, Author

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Chapter 1: 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 polices 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 [46] 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 [17,18,21,22,25]. 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) [7, 9, 11, 12, 27, 33, 45].

Many techniques have already been proposed with the aim of improving spectrum sensing, but mostly for single-band DSA [14–16, 19, 35]. Wideband spectrum sensing has, however, received lesser attention [26, 37, 40]. Most of wideband spectrum sensing techniques leverage compressive sampling theory [6] 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 [6]. In the literature, this sparsity level has usually been set to the average occupancy across the entire wideband spectrum [37, 38]. 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 thesis, 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 [46]. Our technique accounts for the time variability by leveraging supervised learning [43] to provide and use estimates of the sparsity levels, and exploits the block-like spectrum occupancy structure by leveraging compressive sampling [6] 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 thesis 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 this thesis is structured as follows. Related works are presented in Chapter 2. In Chapter 3, we present our system model. In Chapter 4, we describe our proposed scheme. In Chapter 5, we present the performance evaluation of the proposed technique. Finally, we present our conclusion and future works in Chapter 7.

Chapter 2: Related Works

In cognitive radio networks, spectrum sensing is a key task that allows unlicensed users (SUs) to dynamically access the wireless spectrum without harming licensed users (PUs) transmission [17, 35, 47]. This task helps boosting the spectrum utilization as it allows SUs to exploit and take advantage of the spectrum holes/opportunities temporarily unoccupied by PUs [18]. To identify such spectral holes, secondary users may very well use a variety of techniques to determine spectrum occupancy which include energy detection, feature detection, and matched filter detection [49]. However, because accurate sensing can significantly be impacted by severe channel conditions, cooperative sensing has been proposed to take advantage of the built-in spatial diversity of secondary users to accurately detect the state of the spectrum [42]. In a centralized cooperative sensing, idle nodes sense the spectrum and then report their measurements to a separate entity called a fusion center which collects these measurements to perform a centralized, voted decision of spectrum occupancy [48]. Decentralized consensus allows the SUs to locally decide and access the spectrum occupancy without the need for FC while still cooperating with the other SUs locally deduce the spectrum occupancy [20, 22, 30–32, 34]. However, both schemes, when used for wideband spectrum sensing, require high data-acquisition costs due to the need for sampling above Nyquist rates [50]. This is challenging or even impractical due to the limitation in analog-to-digital converters [50].

To address these problems, compressive sampling (CS) has been proposed as a potential solution, as it efficiently takes advantage of the natural sparse occupancy of the wireless spectrum to allow sampling at sub-Nyquist rates [48]. That is, by taking a number of measurements $m(k) \geq O(k \log(n/k)) < n$ where k is the number of occupied channels and n is total number of bands, CS allows to recover the band occupancy. In most of the research works, compressive sampling is applied while $m(k)$ is fixed according to the average number of occupied channels [37, 38]. However, due to the intrinsic time-varying nature of spectrum occupancy, this leads very often to over-sampling or under-sampling. Ideally, the spectrum occupancy should be learned ahead of time using machine learning tools.

The application of machine learning techniques in the context of cognitive radio networks is not new [2, 4, 5, 10, 23, 43]. Authors in [5] surveyed the use of machine learning in spectrum sensing. Authors in [43] 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 [4] considered the case of multiband spectrum where the features are the status of the bands while authors in [3] 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 [26, 37, 38, 40]. 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 [8, 24, 29, 44]. This work aims at leveraging regression models to improve the performance of the cooperative sensing task while not incurring excessive energy and communication overheads.

Chapter 3: System Model

3.1 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 [46]). 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 PU 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.

3.2 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. 3.1, 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 Chapter 4.

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

$$\boldsymbol{r}_i(t) = \boldsymbol{h}_i(t) * \boldsymbol{s}(t) + \boldsymbol{w}_i(t), \tag{3.1}$$

where $\boldsymbol{h}_i(t)$ is the channel impulse between the primary transmitters and the SU, $\boldsymbol{s}(t)$ is the PUs' signal, 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 $r(i) = r(t)|_{t=iT_0}$ 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.

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

$$\boldsymbol{r}_{f,i} = \boldsymbol{h}_{f,i}\boldsymbol{s}_f + \boldsymbol{w}_{f,i} = \boldsymbol{x}_i + \boldsymbol{w}_{f,i}, \tag{3.2}$$

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 $\boldsymbol{x}_i$ can be considered *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 [6].

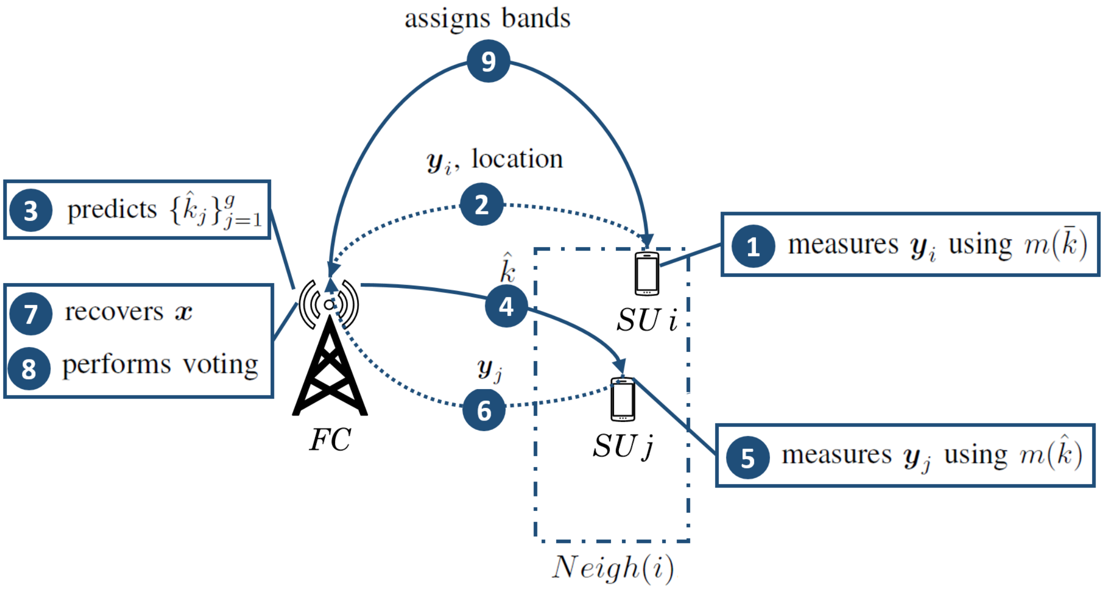


Figure 3.1: Illustration of the cooperative spectrum sensing task.

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 [6]) 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 [6]. Hence, the measured signal can be written as

$$\begin{aligned} \boldsymbol{y}_i &= \Psi \mathcal{F}^{-1}(\boldsymbol{x}_i + \boldsymbol{w}_{f,i}) \\ &= \mathcal{A}\boldsymbol{x}_i + \boldsymbol{\eta}, \end{aligned} \tag{3.3}$$

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.

Chapter 4: 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.

4.1 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 be performed only by and within the region whose SUs need spectrum access.

The proposed cooperative sensing scheme is described as shown in Fig. 3.1. 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 in Equation (3.3). 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 4.3. 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 4.4. 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 [27].

4.2 Special Cases

For completeness of the proposed scheme, we discuss now some of the special cases that may affect the proposed protocol.

4.2.1 Handling requests of neighboring SUs

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.

4.2.2 Absence of Neighboring SUs

The impact of having neighboring SUs is more accurate decision on the occupancy of the wideband. Since FC selects the recent neighboring SUs of $SU\ i$, the SU might have no neighbouring devices. In this case, no benefit of cooperation is achieved. FC compares the estimated spectrum occupancy $\hat{k}$ to $\bar{k}$. If $\hat{k} \leq \bar{k}$, then the taken number of measurement is sufficient for recovering the spectrum occupancy. Otherwise, FC can just request $SU\ i$ to perform $m(\hat{k}) - m(\bar{k})$ measurements. Hence, in this case no benefit is coming from the cooperation but FC ensures that $SU\ i$ has at least taken the required number of measurements.

4.3 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 [6]. 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 to have 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 section, we drop the subscript i of the i^{th} 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.

4.3.1 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 the 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, the more accurate the decision [27].

- *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 $m(\bar{k})$ that SU takes contains a weighted version of the signals in the different bands.

4.3.2 Regression Techniques

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

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 $d = m(\bar{k}) + 4$ 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 $\mathcal{J}(\boldsymbol{w}) = \frac{1}{2N} \sum_{i=1}^{N} \left(\boldsymbol{w}^T \boldsymbol{z}^{(i)} - k^{(i)}\right)^2$.

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 [41]. 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 [41]. 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 [41]. 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 [41]. 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 [41].

4.4 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

$$\omega_i = \frac{1}{\hat{k}_i} / \sum_{j=1}^{g} \frac{1}{\hat{k}_j} \ \forall \ i = [1, ..., g] \tag{4.1}$$

and hence, our proposed recovery approach can be formulated as

$$\begin{aligned} \mathscr{P}(\boldsymbol{x}; \boldsymbol{\omega}) \quad \min_{x} \qquad & \sum_{l=1}^{g} \omega_l \|\boldsymbol{x}_l\|_{\ell_1} \\ \text{s.t.} \quad & \|\mathcal{A}\boldsymbol{x} - \boldsymbol{y}\|_{\ell_2} \leq \epsilon. \end{aligned} \tag{4.2}$$

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.

4.5 Performance Metrics

Our proposed scheme achieves multiple design goals especially with respect to conventional approaches which are:

- **Reducing Sensing Overhead**: In conventional schemes, the sensing overhead is proportional to the total number of secondary users present in that region $\mathcal{O}(K)$. In our scheme, the sensing overhead is considerably reduced to be proportional to $\mathcal{O}(Neigh(i))$.

- **Reducing Sensing energy**: The total sensing energy is measured as

$$\mathcal{E}_{sen} = \|\boldsymbol{y}_i\|_{\ell_2}^2 \tau + \sum_{j=1}^{Neigh(i)} \|\boldsymbol{y}_j\|_{\ell_2}^2 \tau, \tag{4.3}$$

  with τ is the sensing duration. Our scheme achieves two main sensing energy savings. The first energy saving is by using compressive sensing which results on taking less number of measurements. The second energy saving is achieved by reducing to number of cooperating nodes. This results in an overall reduction in the sensing energy besides a reduction in the energy used in reporting the measurements.

- **Achieving higher accuracy**: The benefit of cooperation on the overall accuracy of has been proven in the literature mainly with singe band spectrum sensing and where the spectrum occupancy is the same within a particular cell [27]. Our scheme exploits the same benefit of cooperation but with wideband spectrum sensing. On the top of that, we restrict the cooperating devices to be the neighboring devices since when sensing MMW in 5G which has high attenuations [39], not all SUs have the same observation of the spectrum occupancy.

In the next Chapter, we will evaluate these performance for our scheme.

Chapter 5: Performance Evaluation

Our proposed technique is implemented using Matlab and python. We consider $K = 500$ 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 the users are operating. The used system parameters are summarized in Table 5.1. FC stores the features defined in Section 4.3.1 as well as

Table 5.1: 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

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 [36] to implement the three regression models explained in Section 4.3.2.

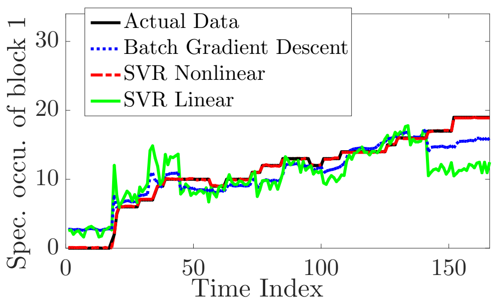
5.1 Evaluation of the Regression Techniques

Figs. 5.1a-5.1d 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 the spectrum occupancy is sparse, time varying, and different from one block to another. Observe 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. 5.2a-5.2d. Overall, observe that the regression technique still follows the same behavior of the actual occupancy of every block. This shows that we do not have a problem of over-fitting which is caused very often by having too many features that lead to high variance.

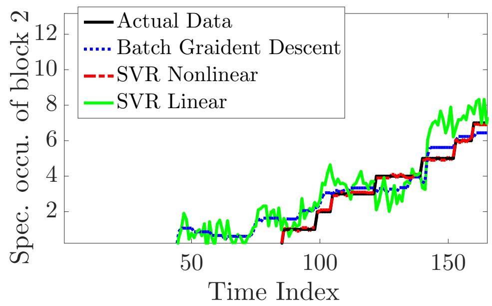
We observe that batch linear regression has a superior performance compared to the other in this case. We also observe that nonlinear SVR still behaves somehow better than the linear models. This is mainly because it gives more accurate support vectors and it deals better with data that is linearly inseparable.

5.2 Evaluation of the Proposed Sensing Scheme

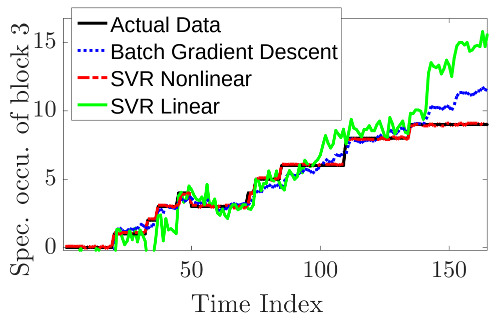
Having assessed the performance of the prediction of the occupancy of every block, we look at the overall performance of our proposed scheme and the effectiveness of the recovery algorithm. We studied the false alarm and the miss-detection probabilities as measures of the effectiveness of our scheme. 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



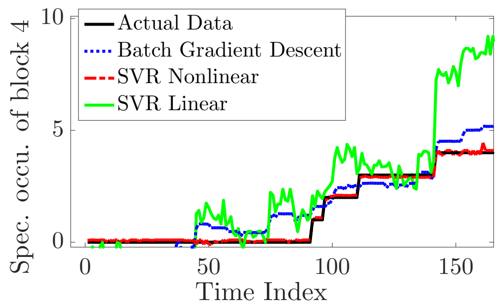
(a) Block 1.



(b) Block 2.

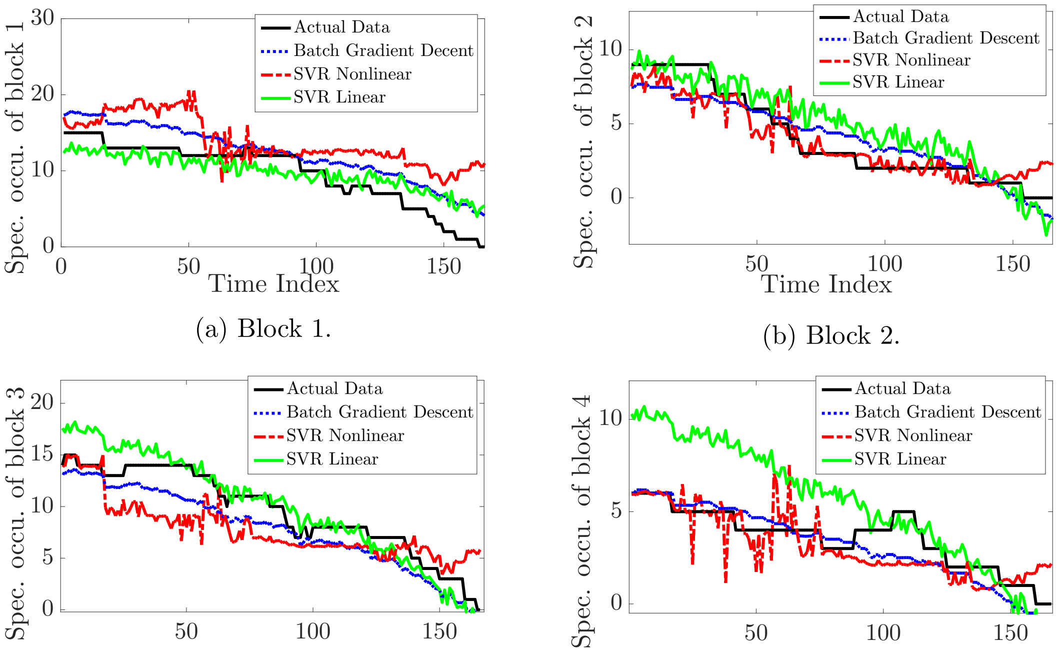


(c) Block 3.



(d) Block 4.

Figure 5.1: Performance of the regression techniques applied to the training data.



(a) Block 1.

(b) Block 2.

(c) Block 3.

(d) Block 4.

Figure 5.2: Performance of the regression techniques applied to the testing data.

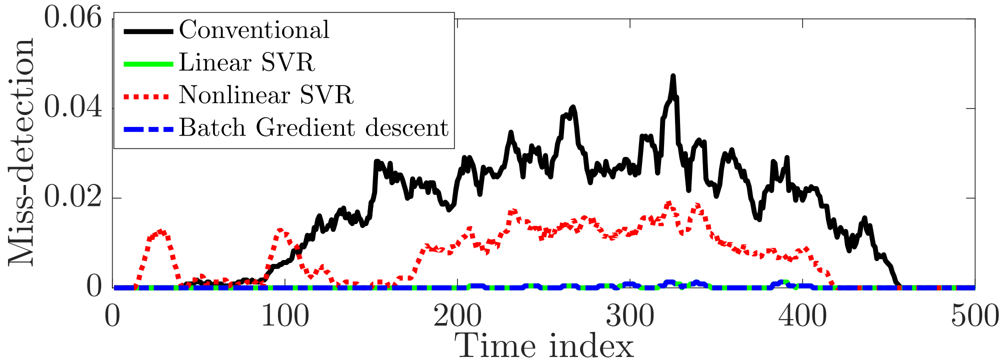


Figure 5.3: Miss-detection performance evaluation of the proposed scheme under the different studied regression techniques compared to conventional approach [37].

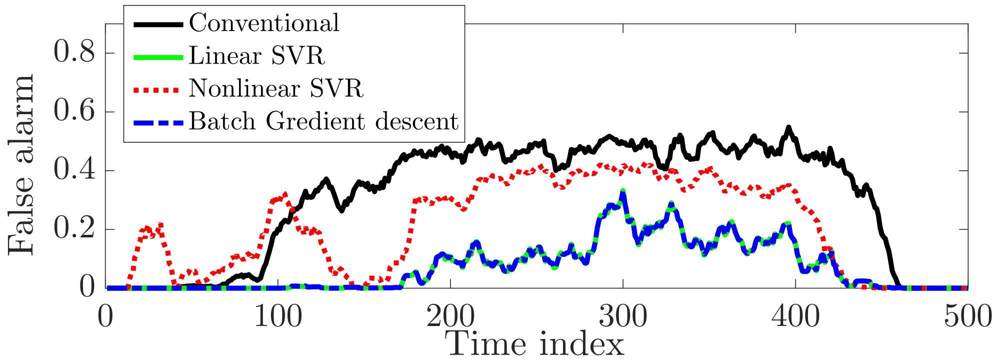


Figure 5.4: False alarm performance evaluation of the proposed scheme under the different studied regression techniques compared to conventional approach [37].

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. 5.3 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. 5.4.

5.3 Evaluation of Overhead and Energy Consumption

As pointed out in section 5.2, our scheme leads to a lower false alarm probability and a lower miss-detection probability than the traditional scheme that utilizes compressive sampling. Now, we look at the cost generated by our proposed scheme in terms of sensing overhead and energy consumption. Fig. 5.5 shows the sensing overhead when applying our proposed scheme against the sensing overhead resulted when using the traditional scheme that relies on all the SUs within the cell. Our proposed scheme outperforms the traditional scheme in this aspect thanks to limiting the cooperating SUs to the neighboring nodes in the proximity of the SU who is willing to access the spectrum.

Following the same trend of the sensing overhead, the resulting reporting energy by the traditional approach is higher our proposed scheme, as shown in Fig. 5.6. In this case, we assumed a $25ms$ reporting time per SU. For the same reason mentioned, the reporting energy is higher in the traditional approach because the traditional approach allows cooperation from all idle SUs falling within the same serving cell with no restriction. However, the proposed scheme favors neighboring nodes that reside in proximity, as these nodes are more likely to observe the same spectrum occupancy.

Fig. 5.7 shows the sensing energy for both the traditional approach and the proposed approach. Assuming a sensing duration $\tau = 25ms$ [13], we looked at the sensing energy observed using the different learning models against the traditional approach. Overall, our system leads to a lower sensing energy than what the traditional approach leads

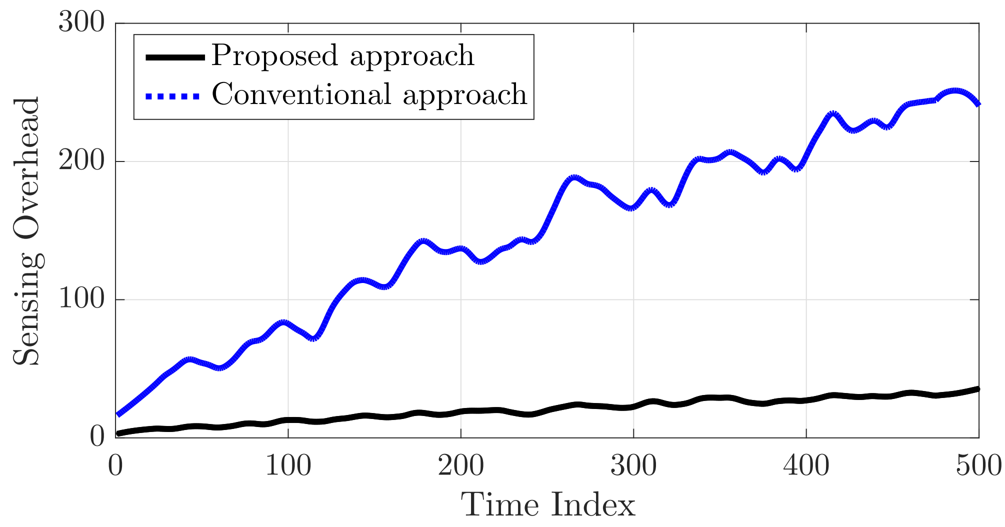


Figure 5.5: Sensing overhead performance evaluation of the proposed scheme compared to conventional approach (not restricting the sensing to the neighboring nodes).

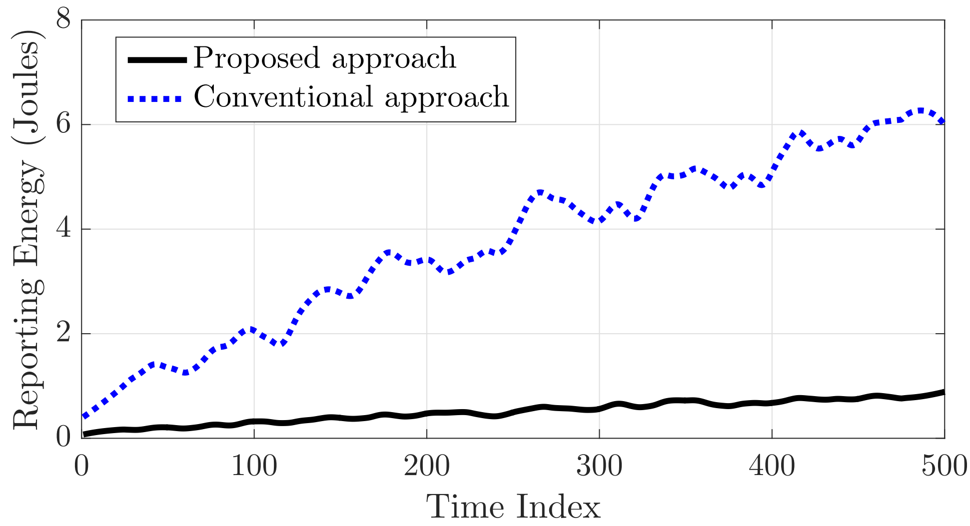


Figure 5.6: Reporting energy performance evaluation of the proposed scheme compared to conventional approach (not restricting the sensing to the neighboring nodes).

to. This stems from two main reasons: $i)$ our proposed models consider the changing behavior of spectrum occupancy and therefore avoids taking unnecessary measurements when spectrum occupancy is low. However, On the other hand, the traditional approach requires taking measurements as a function of the ***average*** spectrum occupancy which, in many instances, leads to an overestimate of the required number of measurements when using compressive sensing algorithm, as defined by $m(\bar{k}) = O(\bar{k}\log(n/\bar{k}))$. $ii)$ In our proposed approach, we restrict cooperation to only include neighboring nodes, and hence, reduces the overall required sensing further.

Furthermore, Fig. 5.7, we can see that gradient descent regression, linear SVR regression, and non-linear SVR regression lead to different sensing energy values, as each of these learning methods provides a different estimate of the spectrum occupancy as discussed in section 5.1.

Fig. 5.8a- 5.8f show the benefit of cooperation in improving sensing accuracy for the different prediction models. We tested the benefit of having larger number of neighboring nodes by testing the performance at different density levels of secondary users, namely at $400/km^2$, $500/km^2$ and $700/km^2$. Figures show that false alarm probabilities and miss-detection probabilities go down as we increase users density. This stems from the fact that the larger the number of neighboring nodes is, the more likely to overcome severe channel conditions between PUs and SUs, the more accurate the overall performance is.

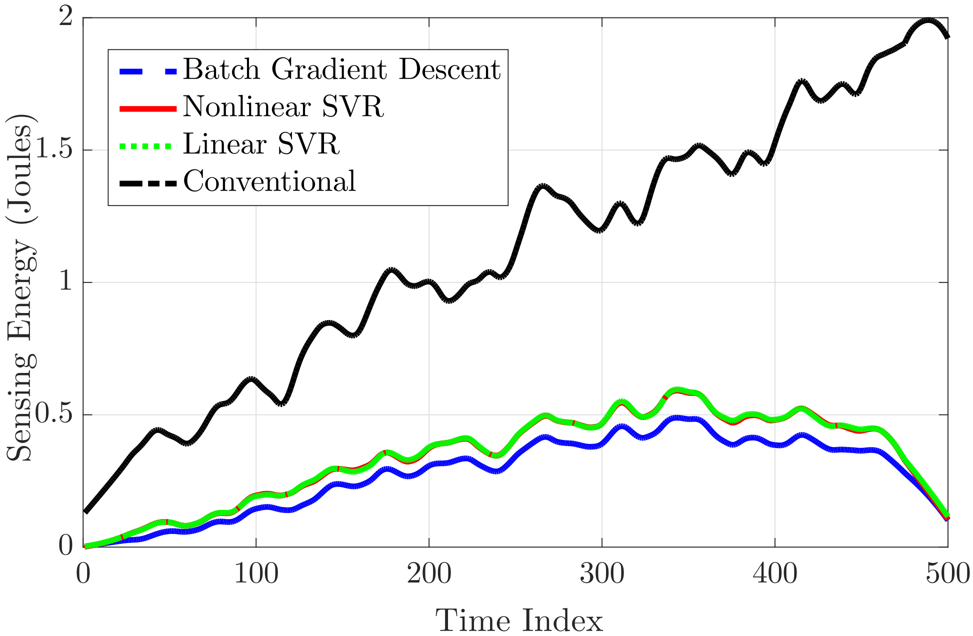
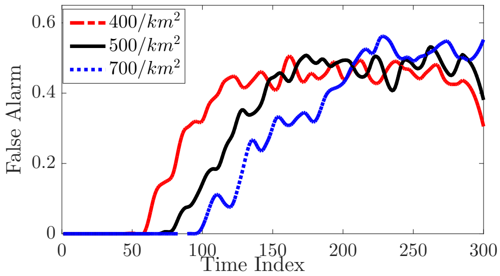
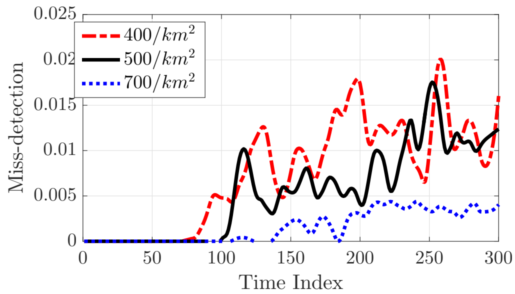


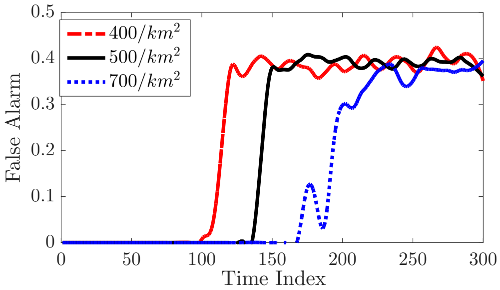
Figure 5.7: Sensing energy performance evaluation of the proposed scheme compared to conventional approach [37].



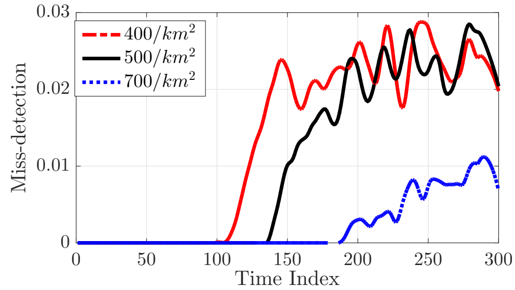
(a) Gradient Descent Regression.



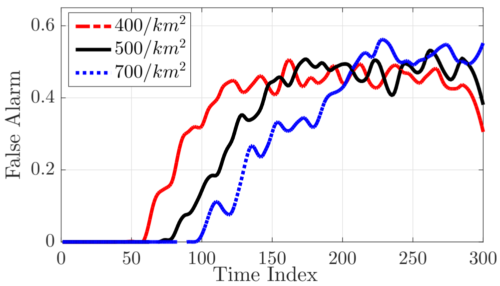
(b) Gradient Descent Regression.



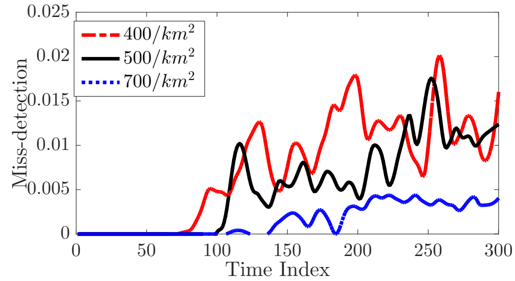
(c) Non-linear SVR Regression.



(d) Non-linear SVR Regression.



(e) Linear SVR Regression.



(f) Linear SVR Regression.

Figure 5.8: Performance of the regression techniques when changing SUs density

Chapter 6: Future Work

I believe that there are several interesting problems that are worth investigating and exploring to further strengthen the results of this thesis. One of these problems is a deeper study of the regression models by studying the features selection problem more closely. Such study can further enhance the ability of the created models to accurately represent the captured data which can potentially lead to a shorter training time and a smaller effect from outliers. Another problem that I believe can increase the efficiency of the adaptive scheme is to learn how often and how frequent the wide band spectrum should be sampled. This require a further study of the traffic of the wide band spectrum. If a robust approach can be made off of it to predict how often to sample the wide band spectrum, this will lead to reducing the number of samples required even further, as the predicted spectrum occupancy from our generated models can be good enough for a number of time slots before it needs to be updated.

Chapter 7: 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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