Efficient Spectrum Availability Information Recovery for Wideband DSA Networks: A Weighted Compressive Sampling Approach

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Abstract—There have recently been research efforts that leverage compressive sampling to enable wideband spectrum sensing recovery at sub-Nyquist rates. These efforts consider homogeneous wideband spectrum, where all bands are assumed to have similar primary user traffic characteristics. In practice, however, wideband spectrum is not homogeneous, in that different bands could present different occupancy patterns. In fact, applications of similar types are often assigned spectrum bands within the same block, dictating that wideband spectrum is indeed heterogeneous. In this paper, we consider heterogeneous wideband spectrum and exploit its inherent block-like structure to design efficient compressive spectrum sensing techniques that are well suited for heterogeneous wideband spectrum. We propose a weighted $\ell_1$-minimization sensing information recovery algorithm that achieves more stable recovery than that achieved by existing approaches, while accounting for the variations of spectrum occupancy across both the time and frequency dimensions. In addition, we show that our proposed algorithm requires a smaller number of sensing measurements when compared to the state-of-the-art approaches.

Index Terms—Wideband spectrum sensing, compressive sampling, heterogeneous wideband spectrum occupancy.

I. INTRODUCTION

SPECTRUM sensing is a key component of cognitive radio networks (CRNs), essential for enabling dynamic and opportunistic spectrum access [1], [2]. It essentially allows secondary users (SUs) to know whether and when a licensed band is available prior to using it so as to avoid harming primary users (PUs). Due to its vital role, over the last decade or so, a tremendous amount of research has focused on developing techniques and approaches that enable efficient spectrum sensing [3]. Most of the focus has, however, been on single-band spectrum sensing, and the focus on wideband spectrum sensing has recently received increased attention [4]–[7].

The key advantage of wideband spectrum sensing over its single-band counterpart is that it allows SUs to locate spectrum opportunities in wider frequency ranges by performing sensing across multiple bands simultaneously. Being able to perform wideband spectrum sensing is becoming a crucial requirement of next-generation CRNs, especially with the emergence of IoT [8] and 5G [9]. This requirement is becoming even more stringent with FCC’s new rules for opening up mm-wave bands for wireless broadband devices in frequencies above 24 GHz [10]. The challenge, however, with wideband sensing lies in its high sampling rate requirement, which can incur significant sensing overhead in terms of energy, computation, and communication. Motivated by the sparsity feature inherent in spectrum occupancy [11] and in an effort to address the high sampling rate limitation, researchers have exploited compressive sampling to make wideband spectrum sensing possible at sub-Nyquist sampling rates (e.g. [5]–[7], [12]–[14]).

These research efforts have focused mainly on homogeneous wideband spectrum, meaning that the entire wideband spectrum is considered as one single block with multiple bands, and the sparsity level is estimated across all bands and considered to be the same for the entire wideband spectrum. However, in spectrum assignment, applications of similar types (TV, satellite, cellular, etc.) are often assigned bands within the same block, and different application types exhibit different traffic occupancy patterns and behaviors. This suggests that wideband spectrum is block-like heterogeneous, in that band occupancy patterns are not the same across the different band blocks. Therefore, sparsity levels may vary significantly from one block to another. This trend that has also been confirmed by recent measurement studies [11], [15]. With this being said, in this paper, we leverage compressive sampling theory [16] to exploit this spectrum occupancy heterogeneity to design efficient wideband spectrum sensing techniques.

A. Related Work

There has recently been a growing interest in using compressive sampling theory [16] to enable wideband spectrum...
sensing [6], [7], [12]–[14], [17]–[22]. A common factor among these works is that the sparsity level is assumed to be fixed over time. In an effort to relax this assumption, Wang et al. [23] propose a two-step algorithm, where at each sensing period, the sparsity level is first measured and then used to determine the total number of measurements. The issue, however, with this approach lies in its computational complexity. To overcome this issue, other efforts have been devoted to developing methods that leverage existing concepts like asymptotic random matrix [20] and stretching [24] theories to estimate these sparsity levels from measurements. There have also been some other efforts [21] that mitigate this realtime change in sparsity levels by proposing approaches that do not require knowledge of these sparsity levels on an instant basis. Such approaches, however, still assume that the sparsity level is bounded and that PU’s signal is wide-sense stationary which is not usually guaranteed in practice.

Other efforts also aimed to exploit additional knowledge about the signal to further improve the sensing information recovery [25]–[31]. For instance, the authors in [25] propose a $\ell_1$-minimization-based recovery approach that exploits knowledge about the support of the sparse signal. The authors in [26] also exploit signal support information, but for recovering signals with noisy measurements. Their technique is shown to be more stable and robust than standard $\ell_1$-minimization approaches when 50% of the support is estimated correctly. This approach has been generalized for multiple weights in [27], addressing the case where the support is estimated with different confidence levels. These approaches, however, work well in applications where the support does not change much over time, like in real-time dynamic MRI [25] and video/audio decoding [26], [27] applications. In the wideband spectrum sensing case where the signal support changes over time, an estimate of the support is too difficult to acquire in advance, making these approaches unsuitable. There have also been attempts that exploit block sparsity information in signals to further improve signal recovery [30], [31]. These attempts, however, were not in the context of wideband spectrum sensing.

Unlike these previous works and as motivated by the block-like wideband spectrum sparsity structure, our proposed framework considers time-varying and heterogeneous wideband spectrum occupancy. We exploit this fine-grained sparsity structure to propose, which to the best of our knowledge, the first spectrum sensing information recovery scheme for heterogeneous wideband spectrum sensing with noisy measurements. We want to emphasize that the use of spectrum recovery methods as the approach for locating spectrum vacancies has benefits over the use of detection methods (e.g., [32], [33]). They, for instance, allow us to determine not only whether there is a signal or not in the wideband, but also which band(s) this signal is occupying. Also, they help to identify the type of signals/devices operating in such bands, a capability of great importance to dynamic spectrum sharing [34]. This work focuses on spectrum recovery methods.

1The support corresponds to the signal components that are non-zero.

B. Our Key Contributions

- We develop an algorithm that exploits spectrum occupancy heterogeneity inherent in wideband spectrum access to provide an efficient spectrum sensing information recovery.
- We prove that our recovery algorithm is more stable and robust than existing approaches, and reduces sensing overhead by requiring small numbers of measurements.
- We derive lower bounds on the probability of spectrum occupancy and use them to determine the sparsity levels that lead to further reduction in the sensing overhead.

It is important to mention that our proposed weighted compressive sampling framework, including the derived theoretical results, is not restricted to wideband spectrum sensing applications. It can be applied to any other application where the signal to be recovered possesses block-like sparsity structure. This includes applications such as sparse target counting and localization [35] and medical imaging and DNA microarrays [30], to name a few. We are therefore hoping that this work can be found useful for solving problems in other disciplines and domains.

The remainder of the paper is structured as follows. In Section II, we present our system model and the PU bands’ occupancy model. Next, our proposed approach along with its performance analysis are presented in Section III. The numerical evaluations are then presented in Section IV. Finally, our conclusions are given in Section V.

II. WIDEBAND SPECTRUM SENSING MODEL

In this section, we begin by presenting the studied heterogeneous wideband spectrum model. Then, we present the spectrum sensing preliminaries and setup.

A. Wideband Occupancy Model

We consider a heterogeneous wideband spectrum access system containing $n$ frequency bands as illustrated by Fig. 1(a). We assume that wideband spectrum accommodates multiple different 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. The wideband spectrum can then be grouped into $g$ disjoint contiguous blocks, $G_i$, $i = 1, \ldots, g$, with $G_i \cap G_j = \emptyset$ for $i \neq j$. Each block, $G_i$, is a set of $n_i$ contiguous bands. Like previous works [36], the state of each band $i$, $H_i$, is modeled as $H_i \sim \text{Bernoulli}(p_i)$ with parameter $p_i \in [0, 1]$ ($p_i$ is the probability that band $i$ is occupied by a PU). Assuming that the bands’ occupancies within a block are independent of one another, then the average number of occupied bands is $\overline{k}_j = \sum_{i \in G_j} p_i$ for $j = 1, \ldots, g$.

Recall that one of the things that distinguish this work from others is the fact that we consider a heterogeneous wideband spectrum; formally, this means that the average number $\overline{k}_j$ of the occupied bands in block $j$ can vary significantly from one block to another. The average occupancies, however, of the different bands within a given block are close to one
another; i.e., \( p_i \approx p_j \) for all \( i, j \in \mathcal{G}_f \). Our proposed framework exploits such a block-like occupancy structure stemming from the wideband spectrum heterogeneity to design efficient compressive wideband spectrum sensing techniques. For this, we assume that the blocks have sufficient different average sparsity levels (otherwise, blocks with similar sparsity levels are merged into one block with a sparsity level corresponding to their average). This is supported by practical observations where typically each block of bands is assigned to a particular application, and the average occupancy could be quite different from one block to another [15], [37], [38]. These averages are often available via measurement studies, and can easily be estimated, or provided by spectrum operators [37].

\[ r_f = h f s_f + w_f = x + w_f, \]  

where \( h_f, s_f, \) and \( w_f \) are the Fourier transforms of \( h(t), s(t), \) and \( w(t) \), respectively. The vector \( x \) contains a faded version of the PUs’ signals operating in the different bands. Given the occupancy of the bands by their PUs (as illustrated in Fig. 1(b)) and in the absence of interference, the vector \( x \) can be considered \textit{sparse}, where a vector \( x \in \mathbb{R}^n \) is \textit{k-sparse} if it has (with or without a basis change) at most \( k \) non-zero elements [39]; i.e., \( \text{supp}(x) = \| x \|_0 = | \{ i : x_i \neq 0 \} | \leq k. \) The set of \( k \)-sparse vectors in \( \mathbb{R}^n \) are denoted by \( \mathcal{K}_k = \{ x \in \mathbb{R}^n : \| x \|_0 \leq k \}. \)

In practice, however, there will likely be interference coming from other nearby cells and users, and hence, \( x \) could rather be \textit{nearly sparse}, where a vector \( x \in \mathbb{R}^n \) is \textit{nearly sparse} (or also compressible [39]) if most of its components obey a fast power law decay. The \textit{k-sparcity index} of \( x \) is then defined as \( \sigma_k(x, \| . \|_{f_s}) = \min_{z \in \mathcal{K}_k} \| x - z \|_{f_s}. \)

Since wideband spectrum is large, the number of required samples can be huge, making the sensing operation prohibitively costly and the needed hardware capabilities beyond possible. To overcome this issue, compressive sampling theory has been leveraged to reduce the number of needed measurements, as the wideband spectrum occupancy vector is sparse or nearly sparse. After performing the compressive sampling, the resulted signal can be written as

\[ y = \Psi \mathcal{F}^{-1}(x + w_f) = Ax + \eta, \]  

where \( y \in \mathbb{R}^m \) is the measurement vector, \( \mathcal{F}^{-1} \) is the inverse discrete Fourier transform since \( x \) is sparse in the Fourier basis, and \( \Psi \) is the sensing matrix assumed to have a full rank, i.e. \( \text{rank}(\Psi) = m. \) Throughout the paper, we consider a uniform sampling where all the coefficients of \( \Psi \) are drawn from the same distribution. Note that while spectrum occupancy heterogeneity in this work is exploited in the recovery, it can also be exploited to design an efficient non-uniform sampling. The sensing noise \( \eta \) is equal to \( \Psi \mathcal{F}^{-1} w_f. \)

It is worth mentioning that without resorting to compressive sampling theory, wideband spectrum sensing requires wideband antennas and Nyquist-rate analog-to-digital converters (ADC), which are very challenging to build [40]–[43]. Compressive sampling overcomes this by allowing sub-Nyquist-rate sampling as illustrated by Fig. 3, where the signal is first amplified by \( m \) amplifiers and mixed with a pseudo-random waveform at a Nyquist rate \( (f_s = 2f_{\text{max}}). \) Then, an integrator is applied followed by an ADC sampling at a sub-Nyquist rate \( (f_s/n) \). The implementation aspects of the
proposed compressive sensing approach are beyond the scope of this paper.

Different from classical wideband compressive sensing, this paper takes advantage of the wideband occupancy heterogeneity to design efficient spectrum occupancy recovery approaches. Specifically, we show that exploiting band occupancy variability across the different blocks indeed improves the recovery accuracy, and thus, the ability to locate spectrum availability.

III. THE PROPOSED WIDEBAND SPECTRUM SENSING INFORMATION RECOVERY

The sensing matrix and recovery algorithm are the main challenging components in compressive sampling design. While the former consists of minimizing the number of measurements, the latter consists of ensuring a stable and robust recovery. In this work, our proposed recovery algorithm outperforms existing approaches by 1) requiring smaller numbers of measurements (better sensing matrix) and by 2) reducing the recovery error (more stable and robust recovery). In this section, we start by providing some background on signal recovery using classical compressive sampling. Then, we present our proposed approach and analyze its performance by bounding its achievable mean square errors and its required number of measurements.

A. Background

The spectrum recovery task can be very computationally costly, a fact that motivated the use of direct signal processing approaches, such as detection [32], [33]. While these approaches succeed in identifying the presence of signals in the wideband spectrum, they fail to locate which portions/bands of the spectrum are occupied/unoccupied. In addition, being able to identify which signal types are occupying the bands is important and can be very useful for DSA applications (e.g., spectrum access policy enforcement) [34]. Such objectives can, however, be achieved via spectrum recovery approaches, which can indicate not only whether there is a signal in the wideband or not, but also which bands are occupied and which signal types are occupying them.

In wideband spectrum recovery approaches, an SU’s aim is to recover the frequency-domain version of the received signal. Exploiting the fact that the signal is sparse, an ideal recovery can be performed by minimizing the $\ell_0$-norm of the signal. This is, however, NP-hard [44]. It turns out that minimizing the $\ell_1$-norm recovers the sparsest solution with a bounded error that depends on the noise variance and the solution structure [16]. This can be formulated as

$$\mathcal{P}_1: \min_{x} \|x\|_{\ell_1} \quad \text{subject to } \|Ax - y\|_{\ell_2} \leq \epsilon$$

(4)

Here, $\epsilon$ is a user-defined parameter chosen such that $\|\eta\|_{\ell_2} \leq \epsilon$. This formulation is known also as Least Absolute Shrinkage and Selection Operator (LASSO) [16].

Although LASSO is shown to achieve good performance when applied for wideband spectrum sensing recovery, it does not capture, nor exploit the block-like occupancy structure information that is inherent to the wideband spectrum, where the occupancy is heterogeneous across the different blocks of the spectrum. As shown later, it is the exploitation of this block-like occupancy structure that is behind the performance again achieved by our proposed recovery algorithm.

B. The Proposed Recovery Algorithm

Intuitively, our key idea is to incorporate and exploit the variability of sparsity levels across the different spectrum blocks to perform intelligent solution search. We essentially encourage more search of the non-zero elements of the signal $x$ in the blocks that have higher average sparsity levels. Such a variability in the block sparsity levels can be incorporated in the formulation through carefully designed weights. More specifically, we propose the following weighted $\ell_1$-minimization recovery scheme:

$$\mathcal{P}^{w}_1: \min_{x} \sum_{i=1}^{g} \omega_i \|x_i\|_{\ell_1} \quad \text{subject to } \|Ax - y\|_{\ell_2} \leq \epsilon$$

(5)

where $x = [x_1^T, \ldots, x_g^T]^T$, $x_i^T$ is a $n_l \times 1$ vector, and $\omega_i$ is the weight assigned to block $l$ for $l \in \{1, \ldots, g\}$. The question that arises here now is how to design and select these weights. Intuitively, the higher the average sparsity level of a block, the greater the number of occupied bands within that block. This means that if we consider two blocks with two different average sparsity levels, say $\bar{k}_1$ and $\bar{k}_2$, such that $\bar{k}_1 < \bar{k}_2$, then to encourage the search for more occupied bands in the second block, the weight $\omega_2$ assigned to the second block should be smaller than the weight $\omega_1$ assigned to the first block. Following this intuition, we set the weights to be inversely proportional to the average sparsity levels. More specifically,

$$\omega_i = \frac{1}{\bar{k}_i} \sum_{j=1}^{g} \frac{1}{k_j} \quad \forall \ i \in \{1, \ldots, g\}$$

(6)

**Remark 1** (Some Insights Into the Proposed Scheme): Consider a two-block spectrum with $\bar{k}_1 > \bar{k}_2$, and hence, with $\omega_2 > \omega_1$. For this special case, the recovery algorithm can then be re-written as

$$\mathcal{P}_{1}^{w,2}: \min_{x} \|x\|_{\ell_1} + \frac{\omega_2}{\omega_1} (\|x_2\|_{\ell_1} - 1) \quad \text{subject to } \|Ax - y\|_{\ell_2} \leq \epsilon.$$
Since we are minimizing the $\ell_1$-norm of $x$ and the $\ell_1$-norm of $x_2$, this can be interpreted as ensuring that the vector $x$ is sparse while ensuring that the portion $x_2$ of $x$ is also sparse (since $\frac{\omega_2}{\omega_1} - 1 > 0$). This means that all solutions that are sparse as a whole but somehow dense in their second portion are eliminated.

Remark 2 (Weights Design): The proposed scheme exploits the per-block average occupancy to improve recovery accuracy. From a practical viewpoint, the per-block average occupancy can be acquired by monitoring the occupancy of each band within the block and averaging them over time [15], [37]. It can also be acquired through prediction approaches, which can provide good estimates. That is said, even when the average occupancy is not determined on a per-block basis; i.e., the entire wideband spectrum is considered as one block, our proposed algorithm becomes equivalent to the classical $\ell_1$-minimization approach (LASSO) (i.e., $P_1$). In other words, our algorithm performs similarly to LASSO when average block occupancies are unavailable and outperforms it otherwise.

In the remaining of this section, we show that our proposed recovery algorithm outperforms existing approaches by 1) incurring smaller errors and 2) requiring lesser measurements.

C. Mean Square Error Analysis

The following theorem shows that our algorithm incurs lesser errors than LASSO [16].

Theorem 1: Letting $x^\dagger$ be the optimal solution for $P_1$, $x^\dagger$ the optimal solution for $P_1$ and $y = Ax_0 + \eta$, we have

$$\|x^\dagger - x_0\|_2 \leq \|x^\dagger - x_0\|_2,$$

with a probability exceeding

$$1 - \sum_{i=1}^{g-1} \sum_{j=i+1}^{g} \sum_{k=1}^{\min(n_1,n_2)} \sum_{l=0}^{k-1} \left(\frac{n_l}{l}\right) q^l_k (1 - q_i)^{n_l - l} \left(\frac{n_j}{j}\right) q^j_k (1 - q_j)^{n_j - k}$$

assuming $n_1q_1 \geq \ldots \geq n_gq_g$.

Proof: The proof is provided in Appendix A.

The theorem says that the solution to the proposed $P_1^{\text{EO}}$ is at least as good as the solution to $P_1$ (i.e., LASSO [16]). Also as done by design, the more heterogeneous the wideband spectrum is, the higher the error gap between our proposed algorithm and LASSO is.

Now, we assess the stability and robustness of the proposed scheme.

Definition 1 (Stable and Robust Recovery [16]): For $y = Ax + w$ such that $\|w\|_2 \leq \epsilon$, a recovery algorithm, $\Delta$, and a sensing matrix, $A$, are said to achieve a stable and robust recovery if there exist $C_0$ and $C_1$ such that

$$\|\Delta y - x\|_2 \leq C_0\epsilon + C_1 \sigma_k(x, ||\cdot\|_{\ell_p}) \sqrt{k}. \quad (9)$$

Note that the stability implies that small perturbations of the observation lead to a small perturbation of the recovered signal. Robustness, on the other hand, is relative to noise; for instance, if the measurement vector is corrupted by noise with a bounded energy, then the error is also bounded [16]. We now state the following result, which follows directly from Theorem 8.

Proposition 2: Our proposed algorithm, $P_1^{\text{EO}}$, achieves a stable and robust recovery.

Proof: The proof is provided in Appendix B.

The proposition gives a bound on the error by means of two quantities. The first is an error of the order of the noise variance while the second is of the order of the sparsity index of $x$.

Remark 3 (Effect of Time-Variability): We want to iterate that our proposed algorithm is guaranteed to outperform existing approaches on the average, and not on a per-sensing step basis. This is because although the performance improvement achieved by our technique stems from the fact that blocks with higher average sparsity levels are given lower weights—which is true on the average, it is not unlikely that, at some sensing step, the actual sparsity level of a block with a higher average could be smaller than that of a block with a lower average. When this happens, our algorithm won’t be guaranteed to achieve the best performance during that specific sensing step. The good news is that first what matters is the average over longer periods of sensing time, and second, depending on the gap between the block sparsity averages, this scenario happens with very low probability.

To illustrate, let us assume that the wideband spectrum contains two blocks with average sparsity $\bar{k}_1 = \sum_{j \in G_1} p_j \approx n_1p_1$ and $\bar{k}_2 = \sum_{j \in G_2} p_j \approx n_2p_2$ with $\bar{k}_2 < \bar{k}_1$, where again $|G_1| = n_1$ and $|G_2| = n_2$. Here, the occupancy probabilities of all bands in each of these two blocks are assumed to be close to one another. Our approach encourages to find more occupied bands in the first block than in the second block. However, since band occupancy is time varying, then at some given time we may have a lesser number of non-zero components in the first block than in the second. This unlikely event, in this scenario, happens with probability

$$\sum_{k=1}^{\min(n_1,n_2)} \sum_{l=0}^{k-1} \left(\frac{n_1}{l}\right) q^l_k (1 - q_1)^{n_1 - l} \left(\frac{n_2}{k}\right) q^k_k (1 - q_2)^{n_2 - k}.$$

For a sufficiently different average sparsity levels (e.g. having $\bar{k}_1 > 2\bar{k}_2$), this probability is smaller than 0.02. Finally, it is worth mentioning that our proposed scheme can achieve further performance improvement by adopting advanced estimation approaches, such as those that are based on machine learning [23]. However, this additional performance improvement comes at the price of additional computational complexity that is accompanied with these estimators.

Having investigated the design of the recovery algorithm, now we turn our attention to the design of the sensing matrix. The number of measurements, $m$, to be taken determines the size of the sensing matrix and hence the sensing overhead of the recovery approach. Therefore, we aim to exploit the structure of the solution to reduce the required number of measurements as much as possible, so that the sensing overhead is reduced as much as possible.
D. Number of Required Measurements

The sensing matrix is usually designed with two major design criteria/goals in mind: reducing the number of measurements and satisfying the RIP property, defined as follows.

Definition 2 (Restricted Isometry Property (RIP) [39]): A matrix \( \mathcal{A} \) is said to satisfy the RIP of order \( k \) if there exists \( \delta_k \in (0, 1/2) \) such that for \( x \in \mathbb{R}^k \)

\[
(1 - \delta_k) \| x \|_2^2 \leq \| \mathcal{A} x \|_2^2 \leq (1 + \delta_k) \| x \|_2^2.
\]

(10)

Broadly speaking, the RIP ensures that every \( k \)-dimensional subspace is almost isometric. Hence, for any \( k \)-dimensional subspace \( \mathcal{S} \), we can recover signals with an accuracy equal to those obtained by existing approaches. Alternatively, we can also say that our framework can recover signals with better accuracy than those obtained via existing approaches.

To address this issue, in our proposed framework, we do not require the actual number of occupied bands to exceed the sparsity level. Instead, the sparsity level that we use in our proposed framework is the average number. Every time this happens, it leads to an inaccurate signal recovery (it yields a solution with high error).

Theorem 3: Let \( \mathcal{A} = [A_1 \ldots A_k] \) be the sensing matrix such that \( A_i \) satisfies the RIP of order \( 2k_i \) with \( \{\delta_{2k_1}, \ldots, \delta_{2k_k}\} \in (0, 1/2). \) Then, the number of measurements \( m \) must satisfy

\[
m \geq \frac{1}{2 \log \left( \frac{\sum_{i=1}^{k} \sqrt{2k_i(1 + \delta_{2k_i}) + \max_i \left( \frac{1}{\delta_{2k_i}} (1 - \delta_{2k_i})/8 \right)} }{\min_i \left( \frac{1}{\delta_{2k_i}} (1 - \delta_{2k_i})/8 \right)} \right)} \times k \log \left( \frac{n}{k} \right)
\]

(11)

Proof: The proof is provided in Appendix C.

Theorem 3 given above provides a lower bound on the required number of measurements needed to recover the signal. As shown later in the result section, this bound is tighter than existing approaches in that with the same number of measurements, our proposed framework can recover signals with better accuracy than those obtained via existing approaches. Alternatively, we can also say that our framework can recover signals with an accuracy equal to those obtained with existing approaches, but while requiring lesser numbers of measurements, \( m \). The derived lower bound exhibits an asymptotic behavior similar to that of the classic bound (i.e., \( O(k \log(n/k)) \)), but with a smaller constant. By setting \( g = 1 \), we get the bound provided in [39, Th. 1.4]. So our derived bound could be viewed as a generalization of that of [39], in that it applies to wideband spectrum with heterogeneous block occupancies; setting \( g = 1 \) corresponds to the special case of the homogeneous wideband spectrum.

Existing approaches determine the required number of measurements by setting the sparsity level to the average number of occupied bands (e.g., \( m \geq k \log(n/k) \)). However, as mentioned earlier, in wideband spectrum sensing, the number of occupied bands changes over time, and can easily exceed the average number. Every time this happens, it leads to an inaccurate signal recovery (it yields a solution with high error).

To address this issue, in our proposed framework, we do not base the selection of the number of measurements on the average sparsity. Instead, the sparsity level that we use in Theorem 3 to determine \( m \) is chosen in such a way that the likelihood that the number of occupied bands exceeds that number is small. The analysis needed to help us determine such a sparsity level is provided in the next section.

E. PU Traffic Characterization

Based on the model of occupancy of the wideband provided in the system model, the following theorem gives the probability mass distribution of the number of occupied bands.

Lemma 1: The number of occupied bands across the entire wideband has the following probability mass function

\[
Pr(X = k) = \sum_{\Lambda \in \mathcal{S}_k} \prod_{i \in \Lambda} p_i \prod_{j \notin \Lambda^c} (1 - p_j)
\]

(12)

where \( \mathcal{S}_k = \{ \Lambda \mid \Lambda \subseteq \{1, \ldots, n\}, |\Lambda| = k \} \), and \( \Lambda^c \) is the complementary set of \( \Lambda \).

Proof: Let \( \Lambda \) the support such that its \( i^{th} \) component is equal to one when there is a PU using the \( i^{th} \) band. Then, the probability that there is exactly \( k \) occupied bands is \( \prod_{i \in \Lambda} p_i \prod_{j \notin \Lambda^c} (1 - p_j) \) such that \( |\Lambda| = k \). Now, considering all the supports with a cardinality \( k \) gives the expression of the mass distribution.

Given this distribution, the average number of occupied bands across the entire wideband spectrum is \( \bar{p} = \sum_{i=1}^{n} p_i \). In the following theorem, we provide a lower bound on the probability that the number of occupied bands is below an arbitrary sparsity level.

Theorem 4: The probability that the number of occupied bands is below a sparsity level \( k_0 \) is lower-bounded by

\[
Pr(X \leq k_0) = \sum_{k=0}^{k_0} \sum_{\Lambda \in \mathcal{S}_k} \prod_{i \in \Lambda} p_i \prod_{j \notin \Lambda^c} (1 - p_j)
\]

\[
\geq 1 - \frac{e^{k_0 - \sum_{i=1}^{n} p_i} k_0^k}{(k_0^{k_0} \sum_{i=1}^{n} p_i)^{k_0}}
\]

(13)

Proof: The proof is provided in Appendix D.

Since the sparsity level is a time-varying process, this theorem gives a probabilistic bound on how to choose a sparsity level such that the level will be exceeded only with a certain probability. Now depending on the allowed fraction, \( \alpha \), of instances in which the actual number of occupied bands exceeds the sparsity level, Theorem 4 can be used to determine the sparsity level, \( k_0 \), that can be used in Theorem 3 to determine the required number of measurements, \( m \). In other words, \( \alpha \) is the probability that the actual number of occupied bands is above the defined sparsity level \( k_0 \). If \( \alpha \) is set to 5%, then it means that only about 5% of the time the actual number of occupied bands exceeds \( k_0 \). As expected, there is a clear tradeoff between \( \alpha \) and \( k_0 \). Smaller values of \( \alpha \) requires higher values of \( k_0 \) and vice-versa. In our numerical evaluations given in the next section, \( \alpha \) is set to 4%.

IV. NUMERICAL EVALUATION

In this section, we evaluate our proposed wideband spectrum sensing approach and compare its performance to the state-of-the-art approaches. Consider a primary system operating over a wideband consisting of \( n = 256 \) bands. We assume that the wideband contains \( g = 4 \) blocks with equal sizes. The average probabilities of occupancy in each block are as follows: \( k_1 = 0.1 \times 64, k_2 = 0.01 \times 64, k_3 = 0.1 \times 64, k_4 = 0.01 \times 64 \). To model the signals coming
from the active users, we generate them in the frequency domain with random magnitudes (which captures the effect of different channel SNRs that every operating PU has with the SU). At the SU side, the sensing matrix $\Psi$ is generated according to a Bernoulli distribution with zero mean and $1/m$ variance. We opted for a sub-Gaussian distribution since it guarantees the RIP with high probability [39]. Here, the number of measurements is generated first according to $m = O(k_0 \log(n/k_0))$. We fix $k_0$ to 25, which ensures that the probability that the actual number of occupied bands is below $k_0$ exceeds 0.96%, as determined by Theorem 4 and plotted in Fig. 4. In the same figure, for completeness, we also show the tightness of the lower bound derived in Theorem 4. Now assuming an RIP constant $\delta_{2k_0} \leq 1/2$ and replacing $k_0$ and the RIP constant with their values in Theorem 3 yields that the number of measurements should be at least 29. We use CVX for the solving of the optimization problem [45].

A first performance that we look at is the mean square error $\|x^\sharp - x_0\|_2^2$ as a function of the sensing SNR defined as $	ext{SNR} = \frac{\|Ax\|_2^2}{\|\eta\|_2^2}$, where $\|Ax\|_2^2 = (Ax)^T Ax$ and $\|\eta\|_2^2 = \eta^T \eta$. In Fig. 5, we compare our proposed technique to the existing approaches. Compared to LASSO [16], CoSaMP [46], and (OMP) [47], our proposed approach achieves a lesser error when fixing the number of measurement $m$ to 27. This is because we account for the average sparsity levels in each block, thereby favoring the search on the first and third block rather than the two others. Also, observe that as the sensing SNR gets better, not only does the error of the proposed technique decrease, but also the error gap between our technique and that of the other ones increases. This is because the noise effect becomes limited. Furthermore, OMP has the worst performance as it requires a higher number of measurements to perform well. In Fig. 6, we look at the performance of the recovery scheme as a function of the average received SNR defined as the ratio between the received signal power and the noise power; i.e., $\|x\|_0^2/\|\eta\|_2^2$. We observe a similar behavior as in Fig. 5.

In Fig. 7, in addition to the random sensing matrix, we show the normalized mean square error of the proposed recovery approach under the Circulant [48] and Toeplitz [49] matrices. Here the elements of the first row of the Circulant matrix and the elements of the first row and first column of the Toeplitz matrix are drawn from a Gaussian distribution with zero mean and $1/m$ variance. The figure shows that random (Bernoulli) matrices outperform Circulant and Toeplitz matrices [50] in terms of achieved errors. This is because Circulant/Toeplitz matrices have lesser incoherent projections than random matrices. In other words, to achieve a robust recovery, the rows of the sensing matrix should have low cross-correlation which is achieved more with a fully random matrix. This superior performance gain comes, however, at the price of a slower recovery compared to Circulant/Toeplitz matrices as shown in [49] and [50].

In Fig. 8, we investigate the error percentage gain (EPG) achieved by our technique when compared to the other schemes under various different numbers of measurements.
We define the error gain of our approach over an existing technique based on compressive sampling. Our proposed technique is a weighted $\ell_1$-minimization recovery approach that accounts for the block-like structure inherent to the heterogeneous nature of wideband spectrum allocation. We showed that the proposed approach outperforms existing approaches by achieving lower mean square errors, enabling higher detection probability, and requiring lesser numbers of measurements when compared to the state-of-the-art approaches.

APPENDIX A

PROOF OF THEOREM 1

Let us consider the average sparsity level in every block to be $k_i = p_i \cdot n_i$ and define the weights as $\omega_j = \frac{1}{k_j}$ (and then we normalize it, as in Equation (6), as $\omega_j = \frac{\omega_j}{\sum_{j=1}^{n} \omega_j}$). Without loss of generality, we assume that $\omega_1 \leq \omega_2 \leq \ldots \leq \omega_g$. First, let us assume to have only knowledge of $k_1$ to have the highest sparsity level in all the blocks. Then, we can consider the recovery problem as

$$\mathcal{P}^{1,1}_{\ell_1}: \text{minimize } \sum_{i=1}^{g} \omega_i \|x_i\|_{\ell_1} + \|x\|_{\ell_1} \text{ subject to } \|Ax - y\|_{\ell_2} \leq \epsilon. \tag{16}$$

Since we have $\omega_1 \leq 1$, this means we encourage the search of more components of $x$ in the first than in the second block. We know that the set of solutions are given by $x_0 + N(\text{null}(A))$. Ideally, its intersection with the $\ell_1$-ball gives the minimizer of $\mathcal{P}$. Now by introducing the weight in the first block, the weighted norm ball will be pinched towards the axis containing $x_1$ which has, in average, lot of non-zero components. Therefore, the recovered vector from $\mathcal{P}^{1,1}_{\ell_1}$ is going to be more accurate than the recovered vector from $\mathcal{P}_{\ell_1}$.

Now, assume to have the knowledge of $1 \leq i < g$ sparsity level of $i$ blocks. Then, the optimization can be written as

$$\mathcal{P}^{i,1}_{\ell_1}: \text{minimize } \sum_{i=1}^{g} \omega_i \|x_i\|_{\ell_1} + \|x\|_{\ell_1} \text{ subject to } \|Ax - y\|_{\ell_2} \leq \epsilon. \tag{17}$$

Applying the same observation, the weighted norm ball is pinched more towards the components of the denser blocks. Therefore, the performance should be at least the performance of $\mathcal{P}_{\ell_1}$. Setting $l = g$, we get $\|x^2 - x_0\|_{\ell_2} \leq \|x^1 - x_0\|_{\ell_2}$. On the other hand, the bands’ occupation is a random process following the bernoulli, then at some given time we may have
a lesser number of non-zero components in the \(i\)th block than in the \(j\)th block with \((j > i)\), the event can be quantified as
\[
\begin{align*}
\sum_{k=1}^{\min(n_1,n_2)} \sum_{l=0}^{k-1} (n_l^i - q_l)(n_j^j - q_j)^{n_j^j - k}.
\end{align*}
\] (17)

Examining all the cases and taking the complementary, we get Equation (8).

**APPENDIX B**

**PROOF OF PROPOSITION 2**

Our proposed approach achieves a stable and robust recovery if we can find \(C_0\) and \(C_1\) such that
\[
\|x^* - x_0\|_{\ell_2} \leq C_0 \epsilon + C_1 \frac{\sigma_k(x, \|\|_{\ell_2})}{\sqrt{k}}.
\] (18)

Combining Theorem 1 and [16, Th. 2], we get (with a probability exceeding \(8\))
\[
\begin{align*}
\|x^* - x_0\|_{\ell_2} &\leq \|x^* - x_0\|_{\ell_2} \\
&\leq C_0 \epsilon + C_1 \frac{\sigma_k(x_0, \|\|_{\ell_2})}{\sqrt{k}}
\end{align*}
\] (19)

where
\[
C_0 = \frac{2(1 + 1/\sqrt{a})}{\sqrt{1 - \delta_{(a+1)k}/\sqrt{a}}}
\] (20)

and
\[
C_1 = \frac{2\sqrt{1 - \delta_{(a+1)k} + 1 + \delta_{a}/\sqrt{a}}}{\sqrt{a}\sqrt{1 - \delta_{(a+1)k} - 1 - \delta_{a}/\sqrt{a}}}
\] (21)

with \(a\) and \(b\) such that \(\delta_{a} + a\delta_{(a+1)k} < a - 1\). Therefore, our approach is stable and robust.

**APPENDIX C**

**PROOF OF THEOREM 3**

Prior to give the proof of the theorem, we start by providing the following lemma.

**Lemma 2:** Let \(k = \sum_{i=1}^{g} k_i\) and \(n = \sum_{i=1}^{g} n_i\) with \(k_i \leq n_i/2\). There exists a set \(X = \bigcup_{i=1}^{g} X_i \subset \Sigma_k\) such that for any \(x = [x_1^T x_2^T \ldots x_g^T]\) with \(x_i \in X_i\) for \(i = 1, \ldots, g\), we have:

1. \(\|x_i\|_{\ell_2} \leq \kappa_i\)
2. For any \(x, y \in X\) with \(x \neq y\), \(\|x_i - y_i\|_{\ell_2} \geq \kappa_i/\sqrt{2}\) and 
\[
\log |X| \geq \frac{n}{2} \log \left(\frac{n}{2}\right).
\]

**Proof:** The proof of the lemma is similar to [39, Lemma A.1]. It is omitted here for brevity.

The proof of the theorem is inspired from the proof in [39] and based on Lemma 2. First, we have \(x = \sum_{i=1}^{g} x_i\) with \(\|x_i\|_{\ell_0} \leq k_i\). Then, for any \(x_i\) and \(y_i\) with \(x_i, y_i \in \Sigma_{2k_i}\), we have according to the RIP property
\[
\sqrt{1 - \delta_{k_i}} \|x_i - y_i\|_{\ell_2} \leq \|A_i x_i - A_i y_i\|_{\ell_2}
\]
\[
\|A_i x_i - A_i y_i\|_{\ell_2} \leq \sqrt{1 + \delta_{k_i}} \|x_i - y_i\|_{\ell_2}
\]
(22)

Combining the above property with Lemma 2, we get
\[
\sqrt{k_i(1 - \delta_{k_i})}/2 \leq \|A_i x_i - A_i y_i\|_{\ell_2} \leq \sqrt{2k_i(1 + \delta_{k_i})}.
\] (23)

By considering the balls with radius \(\tau_i\) such that \(\tau_i = \sqrt{k_i(1 - \delta_{k_i})}/2 = \sqrt{k_i(1 - \delta_{k_i})}/8\) centered at \(A_i x_i\), then these balls are disjoint. On the other hand, we have for any \(x\) and \(y \in \Sigma_{\bar{k}}\),
\[
\|Ax - Ay\|_{\ell_2} \leq \sum_{i=1}^{g} \|A_i x_i - A_i y_i\|_{\ell_2} \leq \sum_{i=1}^{g} \sqrt{2k_i(1 + \delta_{k_i})}
\]
(24)

The upper bound gives an idea about the maximum distance between the centers of any pair of balls which is \(d_{\text{max}} = \sum_{i=1}^{g} \sqrt{2k_i(1 + \delta_{k_i})}\). Therefore, all the balls are contained in the ball of radius \(\tau = d_{\text{max}} + \max_i(\tau_i)\). Thus, we have
\[
\text{Vol}\left(B^n_{\tau}(x)\right) \geq |X| \text{Vol}\left(B^{\min_i(\tau)}\right)
\]
(25)

where \(\text{Vol}(B^n_{\tau}(x))\) is the volume of the ball which is given by \(\text{Vol}(B^n_{\tau}(x)) = \frac{\pi^n/2}{\Gamma(m/2+1)} r^n\) and \(\Gamma(.)\) is the Euler Gamma function. This yields
\[
\left(\frac{d_{\text{max}} + \max_i(\tau_i)}{\min_i(\tau_i)}\right)^m \geq |X|
\]
(26)

Therefore, after applying log, we get
\[
m \geq \frac{1}{\log \left(\frac{d_{\text{max}} + \max_i(\tau_i)}{\min_i(\tau_i)}\right)} \log(|X|)
\]
(27)

Now recalling Lemma 2, we get \(m \geq C_{\delta_1,\ldots,\delta_g} \log(n/k_{\text{avg}})\) where
\[
C_{\delta_1,\ldots,\delta_g} = \frac{1}{2 \log \left(\frac{\sum_{i=1}^{g} \sqrt{2k_i(1 + \delta_{k_i})} + \max_i(\kappa_i(1 - \delta_{k_i})/8)}{\min_i(\kappa_i(1 - \delta_{k_i})/8)}\right)}
\]
(28)

which ends the proof.

**APPENDIX D**

**PROOF OF THEOREM 4**

Let \(Y = \sum_{i=1}^{n_1} H_i\) be the random variable that contains the number of occupied bands. Since the occupation of the band is independent, then the moment generating function of \(Y\) is given by
\[
\mathcal{M}_Y(t) = \prod_{i=1}^{n_1} (e^{t_i} - 1 / p_i).
\]
(29)

Now using the Chernoff bound, we have
\[
\Pr(Y \geq k_0) \leq \inf_{t \geq 0} \left\{ e^{-k_0 t} \mathcal{M}_Y(t) \right\} = \inf_{t \geq 0} \left\{ e^{-k_0 t} \prod_{i=1}^{n_1} ((e^{t_i} - 1)/p_i + 1) \right\}
\]
(30)

Using the fact that \(e^x \geq 1 + x\), we get
\[
\Pr(Y \geq k_0) \leq \inf_{t \geq 0} \left\{ e^{-k_0 t} \prod_{i=1}^{n_1} e^{(t_i - 1) p_i} \right\} = \inf_{t \geq 0} \left\{ e^{-k_0 t} e^{(t_i - 1) p_i} \sum_{i=1}^{n_1} p_i \right\} = \inf_{t \geq 0} \left\{ \left[ e^{(t_i - 1) p_i} \sum_{i=1}^{n_1} p_i \right] \sum_{i=1}^{n_1} p_i \right\}
\]
(31)
To optimize (•), we take the derivative over τ which yields to
\[ t^* = \log(k_0 / \sum_{i=1}^{n} p_i). \]
Now substituting \( t^* \), we get
\[ \Pr(Y \geq k_0) \leq \frac{e^{k_0 - \sum_{i=1}^{n} p_i}}{(k_0 / \sum_{i=1}^{n} p_i)^{k_0}} \]  
(32)
Now since \( \Pr(Y \geq k_0) = 1 - \Pr(Y < k_0) \), we get
\[ 1 - \Pr(Y \leq k_0) \leq \frac{e^{k_0 - \sum_{i=1}^{n} p_i}}{(k_0 / \sum_{i=1}^{n} p_i)^{k_0}} \]  
(33)
which gives the result of the theorem.

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