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Incorporating Primary Occupancy Patterns in Compressive Spectrum Sensing

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ABSTRACT Wideband spectrum sensing remains one of the challenging problems facing the wide deployment of cognitive radio networks. Compressive sensing (CS) was proposed as a promising approach to this problem by utilizing the sparse structure of the underutilized spectrum to capture the spectrum with fewer measurements and simpler hardware requirements. Most of the work in compressive spectrum sensing solely exploits the spatial- and frequency-domain structure of the spectrum neglecting the temporal structure arising from the regularity of primary user (PU) traffic patterns. In this paper, we explore the effectiveness of incorporating PU traffic patterns in compressive spectrum sensing. This achieves improved sensing performance by exploiting the statistics of the PU activity in the CS recovery algorithms. The experimental analysis through simulation shows that the proposed schemes can substantially improve the receiver operating characteristic performance at lower sampling rate noisy spectrum measurements.

INDEX TERMS Compressive sampling, spectrum usage models, wideband spectrum sensing.

I. INTRODUCTION

Cognitive radios (CR) [1], [2] have been gaining increasing attention as a solution to global spectrum scarcity through opportunistic spectrum access. Studies have demonstrated the inefficiency of the traditional radio frequency (RF) spectrum allocation to a single primary user (PU) due to the low utilization of the frequency bands both spatially and temporally. This problem was exalted with the exponentially increasing demand on RF spectrum due to the rapidly expanding markets of multimedia and internet of things (IoT) applications. CR allows for dynamic spectrum access (DSA) [3] for secondary spectrum users (SU) in the interim of the absence of the PU. In order to mitigate interference to the PU, SUs needs to continuously monitor the wireless spectrum in order to detect spectrum holes that are not utilized by their registered PUs. Performing wideband spectrum sensing increases the SU chances to pinpoint vacant bands through searching a wider range of frequency bands. However, it requires sampling the spectrum at a high sampling rate according to the Nyquist theorem. This imposes hardware technological constraints on the needed high-speed analog to digital converter (ADC) and causes an increase in the energy, computation, and communication overhead on the SU terminals.

Compressive sensing (CS) [4] and sparse representation approaches have been successfully applied for reducing data acquisition costs in a wide range of application domains including wireless communication [5]. CS was first proposed as a solution for wideband spectrum sensing in [6]. It allows for sampling the spectrum at sub-Nyquist sampling rate using an analog to information converter (AIC) [7], while using CS reconstruction techniques to efficiently reconstruct the original spectrum through exploiting the sparsity arising from under-utilization. Several approaches were proposed to increase the effectiveness of the compressive spectrum sensing by exploiting additional redundancy in order to further reduce the required sampling rate. This includes using the spatial correlation in cooperative networks [8]–[10] or the geo-location database information [11].

The PU channel occupancy prior information was similarly exploited in several approaches to increase the efficiency of spectrum sensing [12]–[15]. Instead of only assuming the sparsity of the spectrum, these approaches assume some knowledge about the channel occupancy behavior of the primary users. They build on other research foundation of spatial, temporal, and geographic occupancy modeling for

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PU behavior in CR networks and utilize recent results from structured compressive sensing and compressive sensing with side information to incorporate this information into the compressive sensing framework.

In this paper, we propose two compressive spectrum sensing approaches that incorporates the statistical PU channel occupancy pattern to enhance compressive spectrum sensing performance. In the first approach, the occupancy model is used to predict the spectrum support in the next time instant, and the predicted support is used as a prior knowledge in a modified-CS framework [16] to achieve improved reconstruction. In the second approach, statistical information of the channel is used to extract an occupancy likelihood for each channel, which is used to solve a weighted compressive sensing reconstruction problem.

A. RELATED WORK

CS was first proposed as a solution for wideband spectrum sensing in [6] through utilizing the sparse nature of the underutilized spectrum. CS is used to recover the spectrum at a low sampling rate at SU. CS was able to detect the spectrum location with fewer number of measurements. The original CS approaches assume no prior information about the unknown signal except its sparsity [4], [17], [18]. In many applications, prior information is available that can help CS to enhance the reconstruction performance with lower sampling rates.

CS recovery can be modified to take advantage of having statistical information of the signal of interest as a side information to help in reconstruction. The idea of exploiting side information with CS to aid the decoder in recovering the sparse signal with fewer numbers of measurements was the target of a lot of work in the literature.

One of the approaches to exploiting side information in CS is through adding regularization terms and constraints based on the partial support information and/or signal values estimates [16], [19], [20]. By assuming a slow varying nature of the signal support, information from the previous time instant recursively help the reconstruction algorithm to find the sparse solution with fewer number of measurements and decrease reconstruction error in magnetic resonance imaging (MRI). They proposed a modified Basis Pursuit (BP) approach [19] that incorporates known support elements using a weighted $\ell 1$ minimization approach with zero weights on the known support in noise free case and regularized modified-BP to exploit the prior knowledge of the signal values estimates to reduce the reconstruction error. This work was extended in [20] for the noisy case and denoted regularized modified basis pursuit denoising (reg-mod-BPDN).

A different approach of integrating side information with CS was proposed in [21] and [22] and denoted weighted CS. In this approach, a nonuniform sparse models is assumed by dividing the signal support into two sub-classes with different probabilistic prior on the entries being nonzero in each sub-class. This work was later extended into more than two sub-classes in [23] and for arbitrary non-uniform weights in [24]. By finding the proper weights, the weighted $\ell 1$ minimization outperforms the traditional CS in reconstructing the signal with fewer number of measurements.

On the other hand, compressive spectrum sensing with side information was proposed in the literature with several approaches depending on the kind of prior information assumed. The work in [9] exploits the two-dimensional sparse structure when several SUs collaboratively sense a common wide spectrum band. They use Kronecker compressive sensing in order to reduce the sampling rate with lower reconstruction error than conventional CS. Qin *et al.* [11] integrated CS with a geo-location database to improve the accuracy of spectrum sensing in wideband spectrum sensing. In [14], a Bayesian CS with prior estimation of the weight of each signal coefficient, strength and noise precision is utilized to increase the performance of the PU detection.

Another set of approaches [12], [15] assumes a block-like sparsity structure of the wideband spectrum as a result of different occupancy behaviors and patterns for different wireless applications. In [15], assuming prior information about the fixed spectrum allocation, they divided the spectrum into sections with different lengths. They proposed a modified minimization problem in the form of the sum of weighted ℓ_2 norms, with a weighting factor that is iteratively updated. The most relevant to our work is the approach proposed in [12], they exploit the different sparsity levels for different spectrum blocks to determine the weight of each block for weighted CS [23]. By exploiting the knowledge of the sparsity level in each block, their weighted CS approaches achieved more stable recovery than other approaches with fewer number of measurements. However, their approach does not take into account the channel statistical pattern variations within the block.

Finally, channel occupancy modeling was the subject of an extensive set of recent literature studies, as it can greatly improve the spectrum sensing by allowing SUs to forecast the PU occupancy [25]. Different channel occupancy models were proposed in the literature considering time, geo-location, and frequency band occupancy patterns. Time domain occupancy model can be modeled with continuous-time semi Markov chain (CTSMC) with any arbitrary distributions to estimate the idle and busy states holding time of the PU [26]. Beta distribution proved to be a good fit for modeling the frequency domain model through several measurements' campaigns [27], [28]. A spatial duty cycle model was proposed in [29], in order to estimate the average level of PUs occupancy in different geographical location with the knowledge of simple PUs signal parameters in certain period and frequency range.

B. OUR CONTRIBUTION

Our contribution in this paper can be summarized as follows:

- We propose two different approaches for incorporating the PU traffic occupancy patterns into the compressive spectrum sensing paradigm. A predictive approach using modified-CS [16] and a prediction of the occupancy patterns of the PU, and a weighted CS approach [23] that utilizes the occupancy likelihood derived from the PU occupancy model.

- We experimentally prove the effectiveness of the proposed approaches in achieving satisfactory PU detection results with fewer number of measurements. Which in turn can reduce the computation load on limited capabilities SU terminals.
- We study the state-of-the-art PU occupancy pattern models and use it to design effective weights for the proposed weighted CS approach.
- We experimentally validate the robustness of the proposed approaches with respect to PU occupancy model errors.

Finally, this paper offers an attempt for close integration between compressive spectrum sensing approaches and the state-of-the-art PU occupancy modeling. We hope this can be efficiently utilized in future work to develop integrated approaches for simultaneous spectrum sensing and PU occupancy model learning.

C. ORGANIZATION

The remainder of this paper is organized as follows. In section II, we explain our signal and system model and the CS measurement process. The channel occupancy model for the PU traffic patterns is presented in section III. The two proposed spectrum sensing reconstruction approaches are proposed in section IV. Simulation results are presented in section V. We finish with concluding remarks in section VI.

We now establish some important notations. We denote by $N_t = \{1, 2, \ldots, n\}$ the index set of a vector element at the t^{th} time instant in $\mathbf{R}^n$, and $|N_t|$ denotes the number of elements in the set N_t. For any vector $u \in \mathbf{R}^n$, u_i is the i^{th} element of u with $i \in N$, and u_S is a sub-vector which contain the elements of u with indices in S. The complement of any set $S \subset N$ is denoted by $S^c = N \setminus S$, where $\setminus$ means all elements that is found in the set N and not included the set S, and $\varnothing$ denotes an empty set. the support of vector u is written as $Supp(u) = \{i \in N : u_i \neq 0\}$.

II. SIGNAL MODEL AND PROBLEM STATEMENT

We Consider a CR network where each SU terminal locally monitors a wideband of M non-overlapping channels. We assume predefined channel boundaries and unknown power spectrum density levels for the PU of each channel. The problem of spectrum sensing is to determine whether each of these channels is occupied or available for opportunistic use. The channel between any PU and the CR is considered to be a multipath-fading channel with additive white Gaussian noise (AWGN).

Consider I active PUs, whose signals are represented by $\tilde{s}_i(t)$. The received signal at the CR from all PUs can be modeled as follows

$$x(t) = \tilde{x}(t) + w(t), \tag{1}$$

where $\tilde{x}(t) = \sum_{i=1}^{I} \tilde{h}_i(t) * \tilde{s}_i(t)$ is the noise-free received signal from PUs, $\tilde{h}_i(t)$ is the channel gain from the i-th PU to the CR, '$*$' denotes convolution, and $w(t)$ is the additive white Gaussian noise at the CR. Equation (1) can be written in a discrete vector form as follows

$$\boldsymbol{x} = \tilde{\boldsymbol{x}} + \boldsymbol{w} = \sum_{i=1}^{I} \tilde{\boldsymbol{h}}_i * \tilde{\boldsymbol{s}}_i + \boldsymbol{w}, \tag{2}$$

where $\boldsymbol{x}$, $\tilde{\boldsymbol{x}}$, and $\boldsymbol{w}$ are $M \times 1$ vectors.

Taking the discrete Fourier transform (DFT) of (2), the sensed signal can be represented as follows

$$\boldsymbol{X} = \tilde{\boldsymbol{X}} + \boldsymbol{W} = \sum_{i=1}^{I} \tilde{\boldsymbol{H}}_i \tilde{\boldsymbol{S}}_i + \boldsymbol{W}, \tag{3}$$

where $\tilde{\boldsymbol{H}}_i$ is an $M \times M$ diagonal matrix, whose main diagonal is the M point DFT of $\tilde{\boldsymbol{h}}_i$, and $\boldsymbol{X}$, $\tilde{\boldsymbol{S}}_i$, $\boldsymbol{W}$ are the DFT transformation of $\boldsymbol{x}$, $\tilde{\boldsymbol{s}}_i$, $\boldsymbol{w}$, respectively.

Equation (3) can be stacked in a matrix form as

$$\boldsymbol{X} = \tilde{\boldsymbol{H}} \tilde{\boldsymbol{S}} + \boldsymbol{W} = \tilde{\boldsymbol{X}} + \boldsymbol{W}. \tag{4}$$

where $\tilde{\boldsymbol{H}} = [\tilde{\boldsymbol{H}}_1, \tilde{\boldsymbol{H}}_2, \ldots, \tilde{\boldsymbol{H}}_I]$ is an $M \times MI$ matrix and $\tilde{\boldsymbol{S}} = [\tilde{\boldsymbol{S}}_1^T, \tilde{\boldsymbol{S}}_2^T, \ldots, \tilde{\boldsymbol{S}}_I^T]^T$ is an $MI \times 1$ vector. We assume that each PU in the primary network is assigned a different channel, i.e., there is at most one active PU transmitter on each channel. Thus, we can represent the PUs combined spectrum as an $M \times 1$ vector such that $\boldsymbol{S} = \sum_{i=1}^{I} \tilde{S}_i$. We can also construct a combined channel state information (CSI) matrix $\boldsymbol{H}$ as a diagonal matrix, where each diagonal element corresponds to the channel gain between the CR and the active PU occupying this channel. This alternative formulation does not change the sparsity order of the problem. However, the sensed spectrum can now be represented as

$$\boldsymbol{X} = \boldsymbol{H}\boldsymbol{S} + \boldsymbol{W}. \tag{5}$$

In order to estimate the spectrum vector $\boldsymbol{S}$ from the received signal $\boldsymbol{X}$, the CR receiver in compressive spectrum sensing collects a compressed linear combination measurements of the signal samples $\boldsymbol{x}_t$. This can be practically achieved using an analog to information converter (AIC) with much lower sampling rate [7] than the Nyquist rate required by analog to digital converters. The underlying assumption to ensure reconstruction is that the signal is sparse in the frequency domain as the number of occupied channels is much smaller than the total number of channels [17].

CR collects $K \times 1$ time samples measurement vector $\boldsymbol{y}_t$ from $\boldsymbol{x}_t$, where $I < K \ll M$ as follows.

$$\boldsymbol{y}_t = \boldsymbol{\Phi}_t \boldsymbol{x}_t, \tag{6}$$

where $\boldsymbol{\Phi}_t$ is a $K \times M$ random full rank measurement matrix whose entries can be independent and identically distributed random variables drawn from some probability distribution. We chose our measurement matrix to be a Gaussian matrix, where each element is drawn from an independent and identically distributed (i.i.d.) Gaussian random variable with zero mean and $1/K$ variance. It was shown in [17] that such measurement matrix achieves with high probability the restricted isometry property (RIP) condition necessary for reconstruction, with number of measurements K in the order of $O(I \log(M/I)$. Meanwhile, it reduces the required sampling rate by a factor of K/M. Several hardware architecture designs were proposed to efficiently implement such random sensing without the need for high rate ADC, the reader is referred to [5] for complete review of such designs.

Substituting from (5), equation (6) can be rewritten as

$$\boldsymbol{y}_t = \boldsymbol{\Phi}_t \boldsymbol{F}^{-1} \boldsymbol{X}_t = \boldsymbol{\Phi}_t \boldsymbol{F}^{-1} \boldsymbol{H}_t \boldsymbol{S}_t + \check{\boldsymbol{W}}_t, \tag{7}$$

where $\boldsymbol{F}^{-1}$ is the $M \times M$ inverse DFT matrix and $\check{\boldsymbol{W}}_t = \boldsymbol{\Phi}_t \boldsymbol{F}^{-1} \boldsymbol{W}_t$.

In order to detect the spectrum PU presence, we need to recover the spectrum $\boldsymbol{S}_t$ using the minimum number of compressed measurements $\boldsymbol{y}_t$. In this paper, we aim to utilize the knowledge of the statistical spectrum occupancy pattern of the PU to further reduce the sampling rate and enhance the recovery process. In the next section, we will outline the channel occupancy modeling we used in this regard.

III. CHANNEL OCCUPANCY MODELING

PU channel occupancy modeling has recently been an active area of research within the CR literature, it has been used to improve sensing and/or spectrum management through making proactive decisions based on the prior history of the channel. For example, SU can select rarely used channels to reduce the frequency of spectrum handoffs. It is also used to help selecting better channels for control purpose and others for data transmission. Furthermore, statistical information of the spectrum utilization helps to control the transmission power of the CR and reduce interference to the PU.

We model the channel occupancy from both temporal and frequency domains, neglecting the geographically spatial domain for the time being. A time domain model is used to model the arrival and departure of the primary user and the busy/idle periods of the channel. Meanwhile, another statistical model is used to capture the frequency domain statistical correlation between the adjacent channels due to the block-like structure of the heterogeneous wideband spectrum.

Following the work in [30], we model the channel occupancy using a Continuous-Time Semi Markov Chain (CTSMC) model. The channel is considered to be switching between two states. The state s_0 represents the channel being idle and hence available for opportunistic usage. Contrarily, the state s_1 represents the channel being busy with PU activity. The channel remains in either one of the two states for a random time interval denoted as state holding time. However, experimental field measurements have demonstrated that the state holding times do not usually follow the exponential distribution and are more adequately described by other distribution such as generalized Pareto, a mixture of uniform and generalized Pareto, hyper-Erlang, as well as geometric and log-normal distributions [31].

We choose to use the generalized Pareto (GP) distribution to model the perceived lengths of the busy and idle periods. The GP distribution was empirically shown in [31] to be a good fit for channel occupancy modeling for various primary radio technologies especially in low-time resolution observations. Moreover, it was found in [32] to offer higher accuracy and less sensitivity to imperfect spectrum sensing than the other distributions. The cumulative distribution function (CDF) of the state holding times T under the GP distribution is given by:

$$\boldsymbol{F}_{GP}(T; \mu; \lambda; \alpha) = 1 - \left[1 + \frac{\alpha(T-\mu)}{\lambda}\right]^{-1/\alpha} \tag{8}$$

where μ, λ, and α represent the location, scale, and shape parameters, respectively. These parameters satisfy that $T \geqslant \mu$ when $\alpha \geqslant 0$, and $\mu \leqslant T \leqslant \mu - \dfrac{\lambda}{\alpha}$ when $\alpha \leqslant 0$ and $\mu, \lambda > 0, \alpha < 1/2$.

The mean $\mathbb{E}\{T\}$ and the variance $\mathbb{V}\{T\}$ of the state holding times under GP distribution can be calculated from its parameters as follows:

$$\begin{aligned} \mathbb{E}\{T\} &= \mu + \frac{\lambda}{1-\alpha}, \\ \mathbb{V}\{T\} &= \frac{\lambda^2}{(1-\alpha)^2(1-2\alpha)} \end{aligned} \tag{9}$$

One of the straightforward statistical metrics of the PU activity pattern is the duty cycle (DC) of the channel. The DC for a channel denoted Ψ represents the average probability of the channel being busy over time and can be calculated as (10):

$$\Psi = \frac{\mathbb{E}\{T_{ON}\}}{\mathbb{E}\{T_{ON}\} + \mathbb{E}\{T_{OFF}\}} \tag{10}$$

where $\mathbb{E}\{T_{ON}\}$ is the mean holding time for the busy state s_1 and $\mathbb{E}\{T_{OFF}\}$ is the mean holding time for the idle state s_0.

In order to capture the non-homogeneous nature of the wideband spectrum, we categorize the channel duty cycles in the wideband spectrum into different band blocks based on their traffic behavior. It was empirically found through several measurements' campaigns [27], [28] that Beta distribution offers the best fit to model the duty cycle of a group of channels. The probability density function of the Beta distribution is given by:

$$\boldsymbol{F}(x; \alpha, \beta) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1}(1-x)^{\beta-1} \tag{11}$$

where $0 < x < 1, \alpha > 0, \beta > 0$ and $B(\alpha, \beta)$ is the Beta function defined as:

$$B(\alpha, \beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1}\, dt \tag{12}$$

The mean value for the duty cycle can be calculated from the beta distribution parameters as follows:

$$\mathbb{E}\{\Psi\} = \frac{\alpha}{\alpha+\beta}, \tag{13}$$

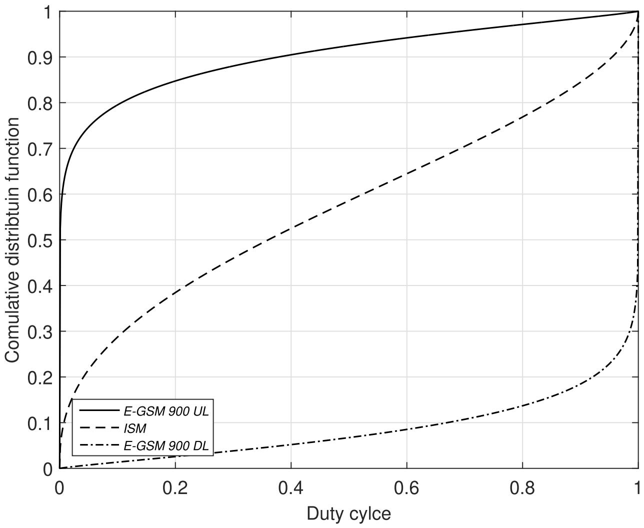

FIGURE 1. **The duty cycle distribution CDF corresponding to different load level wireless sub-band.**

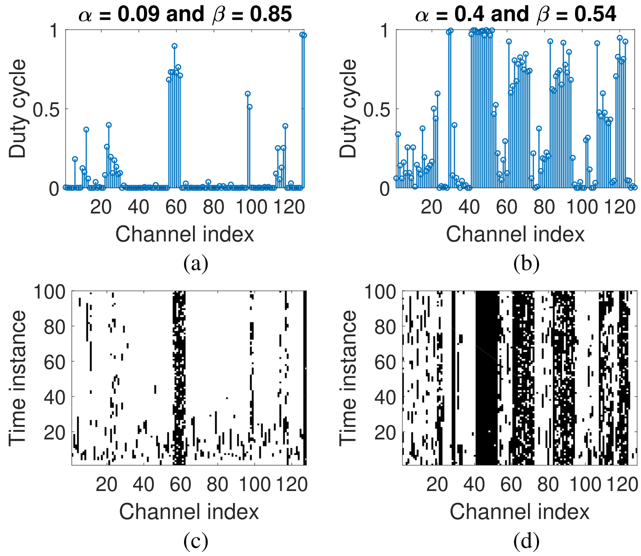

FIGURE 2. **DCs for two different Beta distribution parameters in (a) and (b) with their corresponding time frequency model for PUs activity in (c) and (d).**

The values of the Beta distribution parameters vary for different use cases of the wireless sub-bands, resulting in different distribution of the DC values. Figure 1 illustrate the cumulative distribution function (CDF) of the empirically verified DC distribution for three different load levels, very low PU load with an average DC value of 0.095 (E-GSM 900 UL), medium PU load with an average DC value of 0.42 (ISM), and heavy occupied band with an average DC value of 0.91 (E-GSM 900 DL) [30]. It is worth noting that the beta distribution parameters of the DC are directly proportional to the spectrum sparsity level, with an expected reduced performance of standard compressive sensing approaches in heavy occupied sub-bands.

For certain values of α and β, we generate a set of M different DC values from the Beta distribution. Then, we assign these values of the DC to the various channel taking into consideration that channels with similar occupancy patterns usually occur in groups, with contiguous channels showing strong correlation. In order to model such correlation, we use the DC cluster generation model in [30] to cluster the channels into groups with similar or close value of DC. We first categorize DC values into five different types ranging from very low activity to very high activity, with the set of activity partition values defined at $\{0, 0.05, 0.40, 0.60, 0.95, 1\}$. We then use a geometrically distributed random variable to model the number of contiguous channels per cluster to generate accurate model for PU traffic. The CDF for geometrically distributed random variable is given by:

$$\boldsymbol{F}_{Geom}(k; p) = 1 - (1-p)^k, \quad k \in \boldsymbol{N}^* = \{1, 2, 3, \ldots\} \tag{14}$$

where k is the number of channels belonging to the same cluster and $0 \leqslant p \leqslant 1$ and the value of p can be empirically set from the relation $p \approx M.10^{-3}$ where M the number of the channels of the whole band as long as it satisfies $p \leqslant 1$.

The distribution of the clusters on the whole band is uniformly distributed between the five group types. Taking into consideration that no two adjacent clusters are from the same group type unless it is the only group type available. Resulting in a set $\boldsymbol{\Psi} = \{\Psi_1, \Psi_2, \ldots, \Psi_M\}$ of the DC values for the M channels of the band. Figure 2 illustrates the resulting DC values for 128 channels.

In order to retain a certain DC Ψ_i value for the i^{th} channel, the mean period length of the busy and idle distributions $\mathbb{E}\{T_{ON}\}$ and $\mathbb{E}\{T_{OFF}\}$ are chosen to satisfy the following relation:

$$\mathbb{E}\{T_{OFF}\} = \mathbb{E}\{T_{ON}\}(\frac{1}{\Psi_i} - 1) \tag{15}$$

For each channel, we generate a set of busy state holding times T_{ON} sampled from the GP distribution in (8) for a given location, scale and shape parameters μ_{ON}, λ_{ON}, and α_{ON}, respectively. For each channel, a location $\mu_{i_{OFF}}$ and scale $\lambda_{i_{OFF}}$ parameters for the idle state holding times are calculated form the DC value Ψ_i of the channel as follows:

$$\begin{aligned} \mu_{i_{OFF}} &= \mu_{ON}(\frac{1}{\Psi_i} - 1), \\ \lambda_{i_{OFF}} &= \lambda_{ON}(\frac{1}{\Psi_i} - 1), \\ \alpha_{OFF} &= \alpha_{ON} \end{aligned} \tag{16}$$

Figure 2 illustrates the simulated PU traffic pattern over 100 time instances for two different set of α and β parameters. It clearly shows the effect of the distribution of the DC values on the state holding times for the idle and busy states.

IV. SPECTRUM RECOVERY

In this section, we explain our proposed approach for CR spectrum recovery from the compressed measurements.

The CR senses a compressed set of spectrum measurements as discussed in section II, and recursively recovers the spectrum based on the received signal and the prior information on the spectrum obtained from the channel statistical occupancy model. Our aim is to efficiently incorporate the channel occupancy information in order to efficiently recover the spectrum with a fewer number of measurements.

The system in (7) has infinite number of solutions. However, taking sparsity into consideration, classical CS theory search for the sparsest solution by solving an $\ell 0$ minimization problem, which unfortunately is an NP-hard problem. Replacing the $\ell 0$-norm minimization with the convex $\ell 1$-norm, the program has a feasible solution which converge to the sparsest solution by solving the following basis pursuit (BP) optimization problem [33]

$$\underset{x_t}{\text{minimize}} \ \|\boldsymbol{x}_t\|_1 \quad \text{subject to } \boldsymbol{y}_t = \boldsymbol{\Phi}_t \boldsymbol{x}_t \tag{17}$$

Assuming noisy observation environment, this problem is modified to a Lagrangian variant known as the BP denoising (BPDN) as follows

$$\underset{x_t}{\text{minimize}} \ \|\boldsymbol{x}_t\|_1 + \lambda \left\|\boldsymbol{y}_t - \boldsymbol{\Phi}_t \boldsymbol{x}_t\right\|_2^2. \tag{18}$$

where λ is a penalty parameter, that can be used to trade-off between enforcing the sparsity of the spectrum and minimization of the $L2$ norm term [34]. The smaller λ gets, the more coefficients will be shrunk to zero. The choice of λ affects the performance of the recovery program. Fortunately, λ could be estimated if the noise variance is known as was shown in [33]. The BPDN optimization problem in (18) is very similar to the more common Least Absolute Shrinkage and Selection Operator (LASSO) [35]. Several other alternative CS recovery approaches were presented in the literature such as orthogonal matching pursuit (OMP) [36] and CoSaMP approach [37].

We propose two different CS with side information approaches to incorporate the prior channel occupancy information into the recovery process. In the first approach, we iteratively use the statistical occupancy model to predict a partial support knowledge from the previous sensing instant, which is used to improve the recovery performance of the CS using the Modified BPDN (mod-BPDN) approach [38]. In the second approach, we use the statistical occupancy model to estimate a sparsity confidence level for each band that is used as weights in a weighted CS approach [21].

Consider that the spectrum support (set of occupied channel bands) at time t is represented by $Supp(\boldsymbol{S}_t)$, and N_t denotes its support set representing the index of these channels. Recursive CS algorithms are originally proposed to utilize the spectrum slow varying spectrum pattern in the time domain for some signals. This is achieved in the dynamic regularized version via reducing the search space to find only the sparsest signal outside the previous time instant support. This dynamic (mod-BPDN) recovery problem [38] can be formulated as follows:

$$\underset{x_t}{\text{minimize}} \ \|\boldsymbol{x}_{tT^c}\|_1 + \lambda \left\|\boldsymbol{y}_t - \boldsymbol{\Phi}_t \boldsymbol{x}_t\right\|_2^2. \tag{19}$$

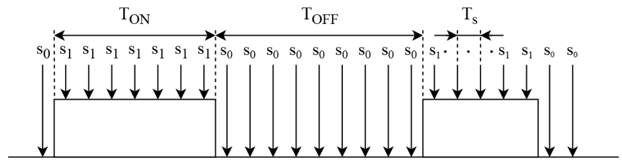

FIGURE 3. States of the channel over a period of time.

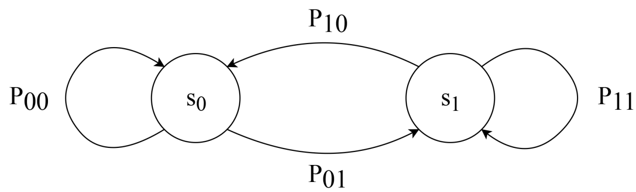

FIGURE 4. Discrete-Time Markov Chain (DTMC) model.

where T is the recovered support set found at the previous time instant $t - 1$.

At each time instant t, the CR captures a measurement of the spectrum as shown in (6). Instead of relying on the support at the previous time instant $Supp(\hat{S}_{t-1}) = \hat{N}_{t-1}$ as in [38], an estimate $\tilde{N}_t$ of the current time instant support is predicted using the channel occupancy model.

Assuming a knowledge of the spectrum at the previous time instant $\hat{S}_{t-1}$. We can identify the status of the channels with decision vector $\hat{d}_{t-1} = \{\hat{s}_{i,1,t-1}, \hat{s}_{i,2,t-1}, \ldots, \hat{s}_{i,M,t-1}\}$, where $\hat{s}_{i,M,t-1}$ denotes the state of the channel M being busy or idle at $t - 1$. The decision vector at the CR is found as:

$$\hat{\boldsymbol{d}}_{t-1} = (\left|\hat{\boldsymbol{S}}_{t-1}\right| > \rho), \tag{20}$$

where ρ is a threshold calculated under Neyman-Pearson detection settings for a given probability of false alarm. This computation requires the knowledge of the noise statistics. It is worth noting that some alternative compressive spectrum sensing approaches such as [10] can avoid this assumption and directly detect the spectrum holes without full spectrum recovery. However, they assume a sequential recovery process where the spectrum signal maintains a fixed support in the frequency domain during the acquisition processes.

Sampling the CTSMC model outlined in the last section with a sampling period T_s, we can generate a sequence of states s_0 and s_1 for the channel being busy or idle as shown in Figure 3. The PU arrival and departure can be simplified by a two-state discrete time Markov chain (DTMC) as shown in Figure 4. The transition matrix for the DTMC is expressed as:

$$\boldsymbol{P} = \begin{bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{bmatrix} \tag{21}$$

where P_{ij} is the probability that the channel transitions from state s_i to state s_j.

It is worth noting that this simplified DTMC model can capture the average occupancy of the channel but fails to characterize the lengths of the state holding times described in the last section.

Assuming a knowledge of the DC values for each channel of the spectrum $\boldsymbol{\Psi} = \{\Psi_1, \Psi_2, \ldots, \Psi_M\}$. We can configure the described DTMC model in (21) to predict the next state of each channel by setting the transition probabilities as $P_{01} = P_{11} = \Psi$ and the $P_{10} = P_{00} = 1 - \Psi$, thus the transition matrix will be on the form:

$$\boldsymbol{P} = \begin{bmatrix} 1-\Psi & \Psi \\ 1-\Psi & \Psi \end{bmatrix} \tag{22}$$

A prediction of the decision vector is writing as $\tilde{\boldsymbol{d}}_t$. Assuming that both $\tilde{S}_t$ and $\tilde{d}_t$ share the same predicted support sets $\tilde{N}_t$, the full spectrum can be recovered from the compressed measurements $\boldsymbol{y}_t$ by solving the following modified BPDN minimization problem [38].

$$\underset{S_t}{\text{minimize}} \ \left\|\boldsymbol{S}_{t\tilde{N}_t^c}\right\|_1 + \lambda \left\|\boldsymbol{y}_t - \boldsymbol{\Phi}_t \boldsymbol{F}^{-1}\boldsymbol{H}_t\boldsymbol{S}_t\right\|_2^2. \tag{23}$$

This optimization problem can be regarded as finding the sparsest signal outside the predicted support $Supp(\tilde{S}_t) = \tilde{N}_t$. Hence, the sparsity of $\boldsymbol{S}_{t\tilde{N}_t^c}$ in the proposed predictive algorithm is reduced to $|\boldsymbol{S}_t| - \left|\tilde{N}_t\right|$. This reduction in sparsity order leads to further reduction in the required number of measurements needed for prefect reconstruction. It was shown in [20], that under Markovian conditions, the solution of (19) becomes a causal MAP estimate. The algorithm of this predictive approach is presented in Algorithm 1.

Algorithm 1 Predictive Scheme

Input:

$\boldsymbol{y}(M \times 1)$, $\boldsymbol{F}(M \times M)$, K

Internal Algorithm Parameters:

$N_0 = \emptyset$ (initial index set)

for $t = 1$ *to* t_{end} **do**

Generate Measurement Matrix: $\boldsymbol{\Phi}_t(K \times M)$

Signal Acquisition: $\boldsymbol{y}_t = \boldsymbol{\Phi}_t\boldsymbol{F}^{-1}\boldsymbol{X}_t = \boldsymbol{\Phi}_t\boldsymbol{F}^{-1}\boldsymbol{H}_t\boldsymbol{S}_t + \check{\boldsymbol{W}}_t$,

Recovery: $\hat{\boldsymbol{S}}_t = \text{minimize}_{S_t} \left\|\boldsymbol{S}_{t\tilde{N}_t^c}\right\|_1 + \lambda\left\|\boldsymbol{y}_t - \boldsymbol{\Phi}_t\boldsymbol{F}^{-1}\boldsymbol{H}_t\boldsymbol{S}_t\right\|_2^2$

Decision vector : $\hat{\boldsymbol{d}}_t = (\left|\hat{\boldsymbol{S}}_t\right| > \rho)$

Predict decision vector for next time instant: $\tilde{\boldsymbol{d}}_{t+1}$

Refine Search Space : $\tilde{N}_{t+1} = \{m \in \{1, 2, \ldots, M\} : \tilde{\boldsymbol{d}}_{t+1} = 1$

Output: $\hat{\boldsymbol{S}}_t$ (total support recovery)

end for

We note here that in the absence of any prior information about free and occupied channels, the spectrum support N_0 is initialized as an empty vector. This for example is used to initialize the algorithm at the first time instant. In this case, this scheme is the same as classical CS approaches, and the minimization problem in (23) reduces to the following unconstrained BPDN minimization program

$$\underset{S_t}{\text{minimize}} \ \|\boldsymbol{S}_t\|_1 + \lambda \left\|\boldsymbol{y}_t - \boldsymbol{\Phi}_t \boldsymbol{F}^{-1}\boldsymbol{H}_t\boldsymbol{S}_t\right\|_2^2. \tag{24}$$

The described predictive approach utilizes the statistical information of the channel occupancy behavior to predict the most probable support set and reduce the dimensionality of the search space, which in turn improves the reconstruction results for the same number of measurements. However, the minimization problem in (23) relies heavily on the prediction accuracy and can cause accumulation of errors over time. This is mainly caused by the complete elimination of the predicted occupied channels form the ℓ_1 search term. On the other hand, the prediction using the simplified DTMC model ignores the characterization of the state holding times which can significantly reduce its accuracy.

Instead of using such prediction for the channel bands, we alternatively propose to use a weighted CS approach [21], where we use the channel occupancy model to impose a weight of every channel for being occupied. The new weighted minimization problem is formulated as follows:

$$\underset{S_t}{\text{minimize}} \ \|\boldsymbol{S}_t\|_{w1} + \lambda \left\|\boldsymbol{y}_t - \boldsymbol{\Phi}_t \boldsymbol{F}^{-1}\boldsymbol{H}_t\boldsymbol{S}_t\right\|_2^2. \tag{25}$$

where the $\|\boldsymbol{x}\|_{w1}$ represents a weighted $L1$ norm given by

$$\|\boldsymbol{x}\|_{w1} = \sum_{i=1}^{n} w_i \mid \boldsymbol{x}_i \mid \tag{26}$$

where x and w is $M \times 1$ signal and positive weight vector.

The optimal choice of the weight vector in weighted CS remains an open problem. However, it is intuitive that higher weights are given to channels with higher likelihood of being unoccupied. Thus, we chose the weights in our spectrum sensing problem to represent the probability of a channel being vacant. Which is directly related to the DC value of the channel based on our CTSMC model (10) in the following way:

$$w_i = P(d_i = s_0) = 1 - \Psi_i \tag{27}$$

It is worth mentioning that the choosing equal weights for all the channels will reduce the optimization problem to the original BPDN program (18). This can be used for example in the absence of accurate estimate of the PU occupancy parameters. In the next section, we evaluate the performance of the two proposed approaches through simulation.

V. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed predictive and weighted approaches in comparison with the original BPDN CS [33], (OMP) [36], and CoSaMP [37] approaches through numerical simulations. In all of our experiments, we consider a spectrum of interest with $M = 128$ sub-channels. The DC values $\boldsymbol{\Psi}$ are sampled as shown in section III form a Beta distribution model configured by the parameters $\alpha = 0.09$ and $\beta = 0.85$ of the E-GSM 900 UL band obtained from [30] and as shown in Figure 2-a, resulting in an average DC value of 0.095. This value is very close to the 10% average occupancy level usually used in compressive spectrum sensing literature. Later in this section, we experimentally investigate the effect of varying the average occupancy level on our proposed algorithm performance. The PU traffic pattern is generated according to GP model configured by the parameters $\mu_{ON} = 100ms$, $\lambda_{ON} = 300ms$ and $\alpha_{ON} = \alpha_{OFF} = 0.25$. A realization of the traffic pattern for 128 sub-channels and 100 time instants was shown in Figure 2-c.

We assume a knowledge of the DC value for each channel, many measurements campaigns where able to extract such statistical information about the spectrum [27]. We will experimentally investigate the effect of inaccurate estimates of the DC values on perfect reconstruction the signal with the predictive and weighted approaches at the end of this section.

The wireless channels between the PUs and the CR are modeled as multipath fading channels with a number of taps $Np = 3$. The gain of each tap is drawn from a Rayleigh distribution. The received signal is corrupted by an additive white Gaussian noise and the signal to noise ratio is considered as the signal power over the entire bandwidth normalized by the noise power. Finally, the compression ratio is defined as the ratio between the number of measurements K and the dimension of the signal M.

Since we are interested in PU detection and spectrum sensing rather than spectrum reconstruction, We evaluate the performance of the different approaches using the ROC curve averaged over 1000 time instants. We note that the probability of detection P_d in our problem refers to the probability of detecting the active PUs, while probability of false alarm P_{fa} refers to marking a channel as occupied while being idle.

Figure 5 shows the detection accuracy of the various approaches at different values of the compression ratios at the same probability of false alarm of 0.1. The results clearly show that the weighted CS approach achieves superior performance and the lowest drop rate in detection probability as we decrease the number of measurements. A noticeable performance gap is evident while using very low rate compressive sampler. This alleviates the need of high cost, high speed ADC, which can be of particular interest to limited capabilities CR devices such as wearable and IoT devices.

The complete ROC curves for the various recovery approaches are shown in figure 6 at SNR value of 5 dB and relatively low compression ratio of 0.3. The results confirm the performance superiority of the weighted approach followed by the predictive approach as compared to the classical CS recovery approaches as it fully exploits our knowledge about the statistical channel occupancy models.

The change in detection accuracy with different SNR values is shown in figure 7 at a compression ratio of 0.3. Again, the weighted approach achieves the highest level of noise immunity as compared other recovery approaches. The predictive scheme still achieves better performance than BPDN, OMP, and CoSaMP. However, it is less prone to errors at low

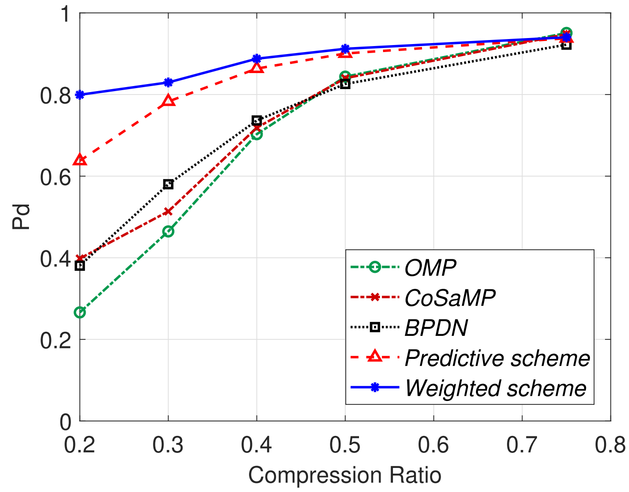

FIGURE 5. Probability of detection at different values of the compression ratio at SNR values of 5 dB and probability of false alarm = 0.1.

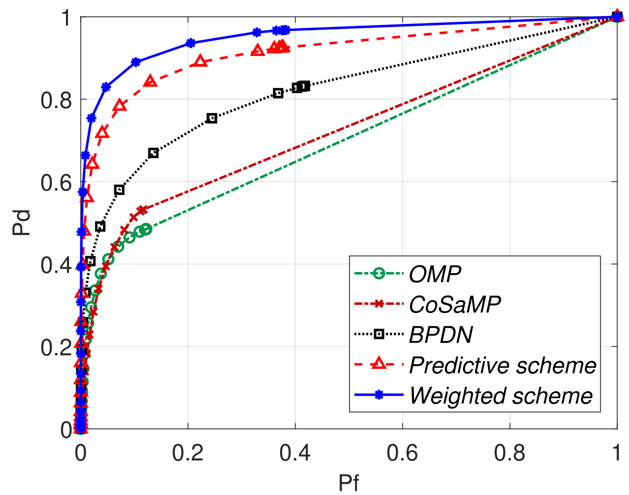

FIGURE 6. The ROC at compression ratio of 0.3 and SNR values of 5 dB averaged over 1000 time instants.

compression ratios due to the accumulation of errors in the estimated support.

All the presented results so far were for the same set of DC configuration parameters, with an average occupancy level of 0.095. In the next experiment we evaluated the effect of different DC configuration parameters on the performance of our proposed approaches. We alternatively sampled the DC values from the different Beta distribution configuration parameters obtained through spectrum measurement campaigns [27], [30].

Figure 8 shows the probability of detection for the various evaluated approaches plotted against the average occupancy level $\mathbb{E}\{\Psi\}$ at compression ratio of 0.5, SNR equals 5 dB, and false alarm probability of 0.1. The values of the PU distribution parameters that resulted in these occupancy levels are obtained from measurement campaign results reported in [27] and [30]. As expected, the performance of all compressive spectrum sensing approaches drops significantly as

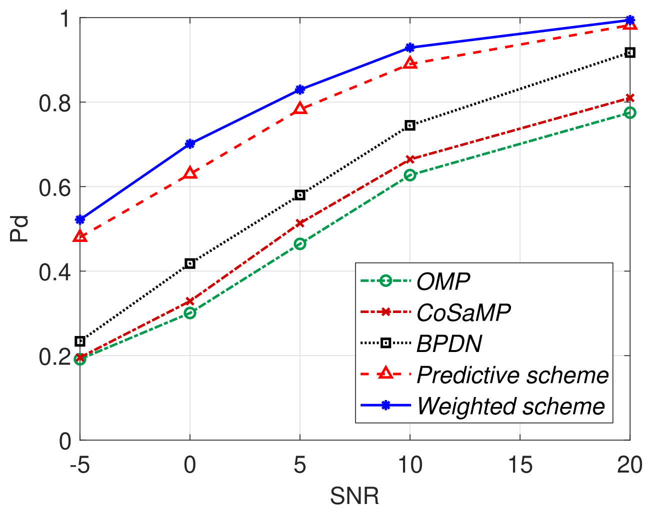

FIGURE 7. Probability of detection at different values of the SNR in dB at compression ratio of 0.3 and probability of false alarm equals 0.1.

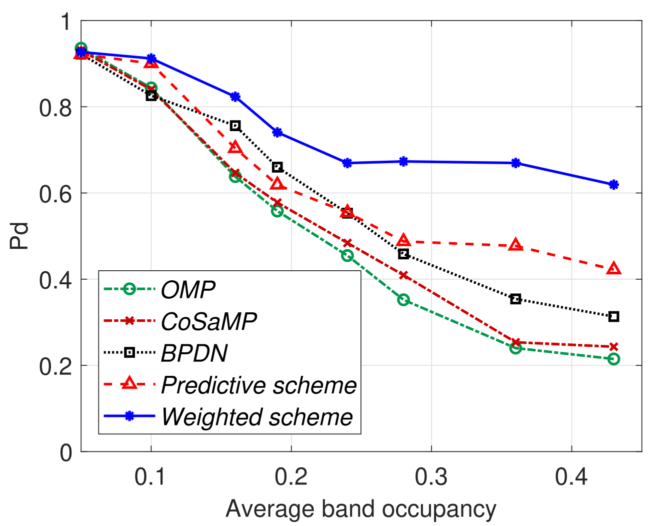

FIGURE 8. Probability of detection at compression ratio of 0.5, SNR equals 5 dB, and false alarm probability of 0.1 for various average occupancy levels obtained from [27] and [30].

we increase the average occupancy levels. This is due to the relative decrease in the sparsity order for the same compression ratio. However, we note that weighted approach achieves the best resilience to increasing the occupancy level, demonstrated by a lower drop rate. This can be attributed to the effect of the weighting on directing the recovery problem into the more likely occupied bands.

In the final experiment, we evaluate the robustness of the proposed approaches to imperfect estimation of the channel occupancy model. An important consideration especially that extracting the statistical information of the spectrum is usually affected by spectrum sensing accuracy. Al-Tahmeesschi *et al.* [32] studied the effect of imperfect spectrum sensing on the statistical time domain occupancy models with different distribution for the idle and busy periods. Comparing the CDF of the estimated

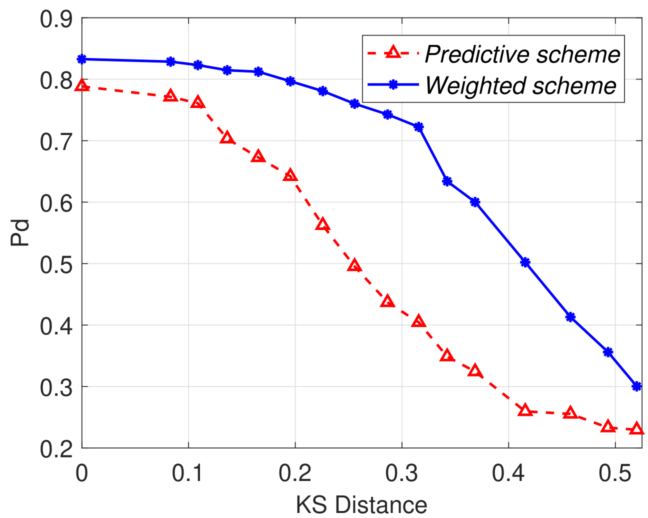

FIGURE 9. Probability of detection for various values of KS distance at compression ratio of 0.3 and SNR value of 5 dB.

distributions with the original ones using the Kolmogorov-Smirnov (KS) distance, defined as:

$$D_{KS} = \sup_{T_i} |\boldsymbol{F}_{T_i}(T_i) - \boldsymbol{F}_{\tilde{T}_i}(T_i)|, \tag{28}$$

where T_i is the original idle and busy periods of the primary user and $\tilde{T}_i$ is the estimated idle and busy periods of the primary user with imperfect spectrum sensing.

We studied the effect of imperfect estimation of the parameters of the GP distribution characterized by different KS distance values on the proposed predictive and weighted spectrum sensing approaches. Figure 9 shows the probability of detection for the two approaches versus the KS distance at false alarm probability of 0.1, compression ratio of 0.3, and SNR = 5 dB. We note that the weighted approach is less sensitive to statistical estimation error than the predictive one in detecting the presence of the primary user.

VI. CONCLUSION

In this paper, we proposed a predictive and weighted approaches for exploiting the channel occupancy statistical models in compressive spectrum sensing. The predictive algorithm predicts the traffic pattern of the PU and use it as a prior information for compressive spectrum sensing. The weighted approach uses the statistical information of the channel to extract the DC value for each channel and use it to solve a weighted compressive sensing problem. The offered weighted approach procedure have evinced a significant performance improvement in term of enhanced ROC with fewer noisy measurements. We studied also the effect of the imperfect spectrum sensing on the proposed approaches. The DC weighted approach proved its immunity to the errors from imperfect channel occupancy modeling.

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