Compressive Spectrum Sensing in Centralized Vehicular Cognitive Radio Networks

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Abstract

Cognitive radio enabled vehicular networks (CR-VNETs) is a new communication paradigm that enables moving vehicles to identify spectrum opportunities along busy streets and freeways. This detected spectrum may possibly lie in licensed frequency bands, and can be used for emergency communications, such as by primary responders during crises events. Spectrum sensing ensures that this spectrum is not currently occupied by licensed users, who have priority access rights. However, as the vehicles are in motion, the spectrum sensing at a given location must be completed with minimum delay, a challenge for classical energy and feature based detection schemes. This paper presents a new distributed compressive sampling technique that allows individual vehicles to report partial information to a centralized base station (BS), with an overhead of only few bytes. Thus, we tradeoff reporting time with processing complexity at the BS, which is tasked with re-constructing the overall spectrum utilization from these portions. Simulation results reveal significant improvements in detection time and accuracy, making our approach suitable for CR-VNETs.

Keywords: *Cognitive radio, spectrum sensing, compressive sampling*

1. Introduction

During times of national emergencies, the existing communication infrastructure used by public safety and emergency responders may get heavily loaded, or suffer from physical damage. This may possibly lead to loss of connectivity at a critical time, owing to lack of spectrum access. Cognitive radio (CR) ad hoc networks enable spectrum access in the vacant licensed bands, thereby allowing continued connectivity among in a decentralized architecture [1]. As emergency responders move to address the crises, they share the roads with other vehicles, each of which is equipped with a cognitive radio connected to a CR base station (BS). The resulting network composed of the CR equipped vehicles, the CR BS and the emergency responders is called as a cognitive radio enabled vehicular network (CR-VNET). Other examples applications of such networks include emergency notification and personal security, vehicle collision avoidance, pre-crash restraint deployment, and automated vehicle operation [2].

FCC regulations in the US allow opportunistic transmission in the digital television (DTV) channels 21-51, except 37, as long as licensed transmissions are not adversely affected. However, the function of spectrum sensing, which is used to identify the vacant spectrum, is a challenge in CR-VNETs. Unlike classical CR ad hoc networks, a node cannot scan multiple channels successively as different regions are covered at subsequent time instants while moving [3]. Thus, nodes in a CR-VNET must rely on wideband sensing to gather the knowledge of the entire spectrum band of interest. This approach in turn raises several concerns in the hardware requirements, especially the sampling rate. Currently available off-the-shelf USRP2 devices can accommodate a maximum of 25 MHz of bandwidth at a time as the signal must be acquired at the Nyquist sampling rate. Analog-to-digital converters (ADCs) that are able to work with large bandwidths (i.e. up to several GHz range), are often prohibitively expensive for wide-scale deployments.

Hence, in order to acquire wideband signal with normal hardware, compressive sampling (CS) [4] becomes a promising solution in realization of cognitive radio. This technique enables us to do the sampling at a much smaller rate than Nyquist rate and accurately reconstruct a sparse signal. The sparseness constraint is easily satisfied in practical CR-VNETs. Recent measurements have shown that the spectrum utilization in a large portion of the licensed GHz range of frequencies is within 0-5% outside city limits [5]. Roads and highways often pass through regions of moderate to low population density, such as rural areas, which typically observe low spectrum usage. Finally, several prior works have stressed that only few channels of interested spectrum are occupied by the licensed or primary users (PUs) making CS an attractive option [6-8].

The first effort of implementing CS for spectrum sensing was introduced in [6]. The spectrum estimation is obtained using a wavelet edge detector after signal recovery. However, this scheme only works for special signal whose Fourier transform is real. The effect of applying analog-information converter to wavelet detector is explored in [7], wherein the high computational complexity is still a problem. Noting that the PU signal in a distributed CR network is sparse, [8] exploits the sparsity difference between PU signal and the signals emitted by the other CR nodes. Nevertheless, all the aforementioned works require every single CR user to undertake CS in each sensing period. This imposes considerable amount of time for sensing for a vehicle, with costly hardware, thus limiting its practicality for CR-VNETs.

The novel contribution of our proposed scheme is as follows: Each CR user only sends in a single scalar value (*i.e.*, a single inner product between network-wide pre-decided constant matrix Φ and the digital PU signal). K different measurements are obtained simultaneously by K distinct users. The BS collects the measurements results to reconstruct the frequency domain information of the sparse PU signal through CS, which is finally used to obtain the wideband spectrum occupancy status. Thus, the complete inference burden is shifted to the BS, and only part of the local computation is provided by the CR users.

The remainder of the paper is organized as follows. In Section II, the preliminaries of CS and the CR-VNET network model are presented. Section III describes the proposed centralized CS-based spectrum sensing scheme. We undertake a thorough performance evaluation in Section IV, and finally, Section V concludes our work.

2. Preliminaries

2.1. Compressive Sampling Basics

Compressive sampling is a method to recover signals from far fewer measurements than needed for traditional sampling. We represent the analog signal $x(t)$, $0 \leq t \leq T$ as a finite weighted sum of a orthonormal basis $\phi_i(t)$ as follows

$$x(t) = \sum_{i=1}^{N} s_i \phi_i(t) \tag{1}$$

where only a few basis coefficients s_i are much larger than zero due to the sparsity of $x(t)$. In particular, with a discrete-time CS framework, consider the acquisition of an $N \times 1$ vector x. Also, suppose that there is an orthonormal basis Ψ in which x is T sparse, i.e. where only T basis coefficients are much larger than zero due to the sparsity of x. Mathematically, x can be written as [4]:

$$x = \Psi s \tag{2}$$

Compressive sampling theory states that $\boldsymbol{x}$ can be accurately recovered from $K \ll N$ measurements of the signal. Assume that we use a set of K linear combinations of the signal as the measurement vector y

$$y = \Phi x \tag{3}$$

where Φ is the constant and known sensing matrix of dimension $K \times N$, where K is the number of independent measurements (or reporting CR users), and N is the length of received signal $\boldsymbol{x}$. Then by properly choosing Φ, and based on sparsity of the representation of $\boldsymbol{x}$ in the Ψ basis, $\boldsymbol{x}$ can be recovered from $\boldsymbol{y}$. As the basis matrix is determined by the nature of the problem, choosing a sensing matrix having a low coherence (incoherent) with Ψ will lead to a smaller K. This suggests choosing Φ to be a totally random matrix [4]. More specifically, T sparse and compressible signals of length N can be recovered from only $K \geq cT \log (N/T) \ll N$ random Gaussian measurements, where c is a small constant. Then reconstruction can be achieved by solving the $\ell 1$ norm minimization [4]:

$$\hat{s} = \arg\min_{s} \|s\|_1 \ \text{s.t.} \ y = \Phi \Psi s \tag{4}$$

2.2. Network Model

We consider a four-lane highway in a rural setting, as shown in Figure 1. The multiple BSs can be installed on existing light poles, traffic signals and road signs along the road with constant separation, here assumed as 150 meters. We assume the traffic density of the road is 30 vehicles per mile per lane according to [9], which equals to approximate 40 cars in the coverage of a BS. The CR users (cars) sample the received PU signal simultaneously and report the measurements to BS. The BS obtains the final spectrum sensing results, and broadcast them to all the nodes in its range. Recent measurements have shown the DTV PU on/off time having mean of 63.6 seconds [10], which renders the network to be virtually static for a round of given measurement and decision dissemination.

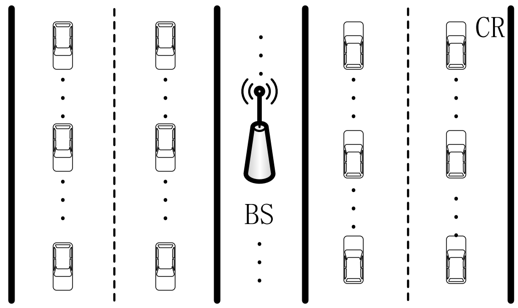

Figure 1. Vehicular cognitive radio network model

The total DTV frequency range is composed of 30 non-overlapping contiguous channels, whose bandwidth and center frequency are invariant and known to all users. We assume each user is using a wide-band antenna listening to the whole spectrum and providing the node with the wideband time domain signal $x(t)$. Unlike the conventional system, the users in our proposed model do not need to have the energy detector. Each user is only equipped with a multiplier to conduct the inner product operation rather than undertake signal energy integration and comparison, which can significantly reduce the hardware complexity.

The network provides a dedicated error free common control channel (CCC), which is used to report sampling information and broadcast sensing results. We assume that CR users report their information using the classical CSMA-based RTS/CTS scheme.

3. Proposed Compressive Spectrum Sensing Technique

Before we discuss the details of our centralized scheme, we would like to comment on the feasibility of the recent FCC ruling on spectrum databases [11]. Here, the CR devices must have positioning capabilities, and are required to download the region-specific occupancy from a database. Thus, they are not required to perform additional sensing before transmitting.

We compared the results from main dynamic DTV band databases [12-14] for four locations in Massachusetts, which are presented in Table I. We can find there are considerable differences between the number of channels stated to be free out of a maximum of 50 in the DTV band. The FCC map [12] consistently provides details of some of the channels, but does not mention the status of many of the others. The other two databases [13-14] list all the channels, but lack consistency among them. Thus, there is a necessity to perform efficient spectrum sensing before transmitting, given the state of existing spectrum databases.

Table 1. TV White Spaces Results from Databases

Location	Number of idle channels[12]	Number of idle channels[13]	Number of idle channels[14]
Boston	25	3	13
Newbury	33	9	15
Westford	23	6	5
Carver	28	7	16

Apart from highlighting the database inconsistency, Table 1, also points out the sparseness in spectrum occupancy in *comparatively* rural areas, such as Newbury and Carver, MA, U.S.. In such areas, we apply CS theory to realize the proposed wideband spectrum sensing paradigm.

The proposed distributed CS processing scheme is depicted in Figure 2. Recall that the matrix Φ is of dimension $K \times N$, determined by the number of CR users (K) and the length of received signal (N). Let each element of the matrix Φ be represented by ϕ_{ij} (i=1,…,K, j=1,…,N), which are generated through a random Gaussian process. In the measuring period, each CR_i undertakes the inner product operation once (rather than K times) between the stored sensing matrix vectors ϕ_{ij} and the PU signal x to get required K measurements y_i. Finaly, the BS reconstructs the frequency domain information f_m (m=1, … , M) by solving the linear convex optimization problem. Thus, it obtains the entire spectrum occupancy status based on f_m and broadcasts the results within the network.

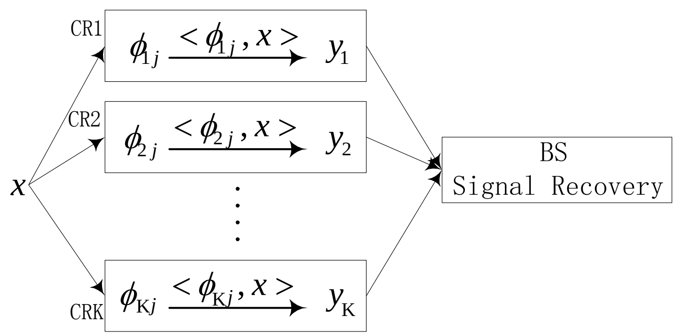

Figure 2. Centralized Cooperative Compressive Sampling Scheme

CR users report their measurements synchronously in every sensing period, and then await for the broadcasting of the sensing results from the BS.

For the sampling procedure, we denote (3) as following

$$y = \Phi x = \begin{bmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{1N} \\ \phi_{21} & \phi_{22} & \cdots & \phi_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \phi_{K1} & \phi_{K2} & \cdots & \phi_{KN} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_K \end{bmatrix} \tag{5}$$

where ϕ_{ij} are the elements of the measurement matrix; $\boldsymbol{x}$ and $\boldsymbol{y}$ are the $N \times 1$ and $K \times 1$ vectors of the PU signal and sampling measurements respectively. From (4), we define our signal recovery problem as follows:

$$\hat{f}_m = \arg\min_{f} \| f_m \|_1 \quad \text{s.t.} \quad y = GF^{-1} f_m + n_f \tag{6}$$

where $y = GF^{-1} f_m$ is the specific expression of $y = \Phi\Psi s$. Here $G = \Phi$ is the random Gaussian measuring matrix, F is the discrete Fourier basis and n_f is the noise sample vector that remains to be white Gaussian. $F^{-1} f_m = \Psi s = x$ is the frequency domain expression of received signal.

In general, we use $f = CS(y;\Phi)$ to represent a signal recovery algorithm for solving the sparse vector f in a linear regression model $\boldsymbol{y} = \Phi f + n$, where n is additive white Gaussian noise (AWGN). In this notation, the local spectral estimation solution to (6) can be expressed as:

$$\hat{f} = CS(y; GF^{-1}) \tag{7}$$

Note that the application scenario assumed in a CR-VNET network is not interested in the PU signal strength, but simply wishes to know which of the channels are unoccupied. In this case, the spectrum sensing task is reduced to spectrum detection. Based on the recovered frequency domain information of the PU signals, the BS will make the available idle channel decision by detecting a binary state vector $d \in \{0, 1\}^{M \times 1}$, whose m-th element is defined by

$$d(m) = \begin{cases} 1, & if\ \ channel\ m\ is\ occupied \\ 0, & if\ \ channel\ m\ is\ ilde \end{cases} \tag{8}$$

The decision on (8) can be made by comparing the local spectral estimate $\hat{f}_m$ obtained in (6) with a decision threshold λ_m:

$$d(m) = (\left|\hat{f}_m\right| > \lambda_m) \tag{9}$$

The threshold λ_m can be chosen based on a desired level of probability of false alarms P_f, using the well-known Neyman-Pearson binary hypothesis test rule [15].

4. Performance Analysis and Simulation Results

In this section, we study the behavior of CS based spectrum sensing under the scenarios of (i) 30 CRs in the BS coverage area and (ii) 40 CRs in the BS coverage region, typical for vehicular networks. There are 30 non-overlapping DTV channels for the CR operation, each of 6MHz bandwidth. We randomly choose 3 channels to be occupied by single tone PU signal of length 1.6667×10^{-5}s, which makes the time-bandwidth product to be 100 per channel. The decision threshold λ_m in (9) is chosen as NP rule such that the false alarm $P_f = 0.05$. The SNR of the received signal is varying from 0dB to 15dB.

In our study conducted in MATLAB, we use two classical approaches for comparison: a one-bit hard and soft combination cooperative sensing schemes. In one-bit hard cooperation scheme, CR users only send their 1 bit detection results to BS. While, the integrated energy information is reported to BS in soft combination scheme, which is proved having the optimal sensing accuracy [3, 16]. Here, we focus on two important metrics: the time consumed for detection, and the detection accuracy by measuring the – (i) total detection time, which includes the sampling time and reporting time, (ii) the processing time at the BS, (iii) the memory requirement for storing the sampling results, and (iv) the detection probability.

As conventional spectrum sensing schemes undertake sequential detection for wideband spectrum, we use AND fusion rule to determine the entire spectrum detection probability, which means the detection is correct only when all the channels status are detected accurately. Let denote AND rule by:

$$P_d = \prod_{i=1}^{30} P_{d,i} \tag{10}$$

We use 802.11 analytical model to simulate the measurements reporting time [17]. The MAC header, PHY header, ACK, RTS, CTS, Bit rate and propagation delay of CCC are set to be 272 bits, 128 bits, 240 bits, 288 bits, 240 bits, 1Mbit/s and 1 μs respectively. The one-bit hard sensing scheme sends a single bit decision over the CCC, while other two schemes send 32 bits. The processing times are measured on milliseconds.

Table 2 and Figure 3 show the detection performances of different sensing schemes in scenario (i). We observe that the proposed sensing approach has overwhelming advantage on detection time compared to classical sensing schemes as it is capable of detecting the entire spectrum in one sensing period rather than channel by channel searching. The processing time tradeoff in CR-VNET allows the BS to incur the computational overhead of spectrum decision, which can be further optimized using high speed processors. In addition, each CR user in our scheme requires only 1 unit measurement storage memory, which reduces the hardware complexity and energy consumed for vehicles. However, the detection probability of compressive spectrum sensing does not reach the requirement of 90% for 30 users.

Table 2. Detection Performances of Three Sensing Schemes

	Hard	Soft	CS
Detection time	1296.7	1324.6	44.5
Processing time(BS)	3.2	0.1	2075
Memory requiring	100	100	1

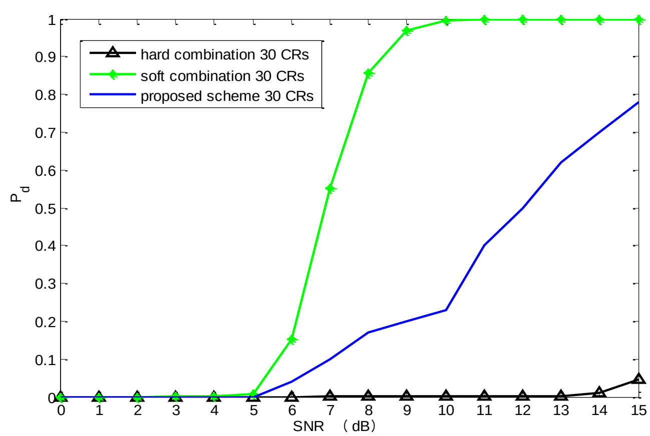

Figure 3. Detection Probability of Different Schemes in Scenario (i)

We observe that with the increasing of numbers of CR users to 40 (Table 3 and Figure 4), the detection probability of proposed scheme is improved significantly. Thus, we can meet the accuracy requirement when the SNR is higher than 13dB. The fast wideband sensing technique of our proposed approach ensures the efficient spectrum utilization in CR-VNET in most practical signal and noise settings.

To study the detection accuracy of CS based spectrum sensing, we continuously vary the fraction of occupied channels on the x-axis from 3/30 to 10/30 and the number of CR users on y-axis from 20 to 90, and measure the detection probability under different situations depicted in Figure 5. As more PUs become *active*, we observe that higher number of CR users need to be added to maintain the required spectrum sensing accuracy. Conversely, increasing CR users can improve the detection performance, when the number of PUs is constant. This can happen practically in CR-VNET, when vehicles get densely packed in a traffic jam in an emergency event. This higher density will also result in enhanced sensing accuracy, as more vehicles get involved in sensing.

Table 3. Detection Performances of Three Sensing Schemes

	Hard	Soft	CS
Detection time	1751.1	1788.2	60.0
Processing time(BS)	3.4	0.1	2227.0
Memory requiring	100	100	1

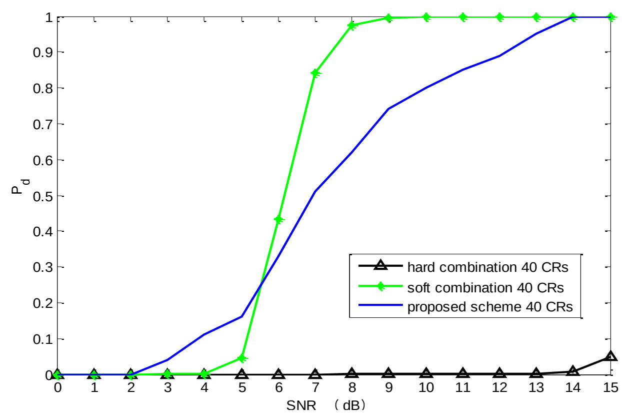

Figure 4. Detection Probability of Different Schemes in Scenario (ii)

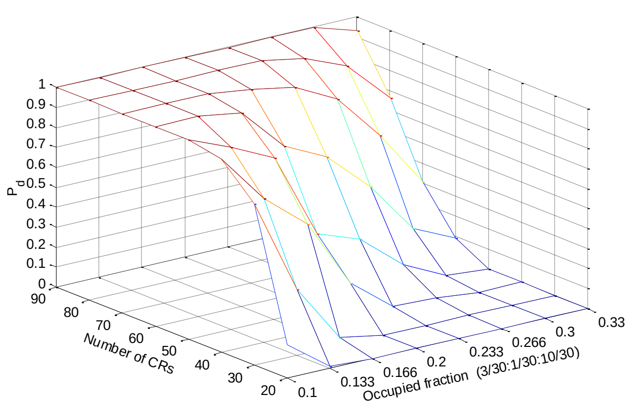

Figure 5. Sensing probability of Proposed Scheme under Different CR Numbers and Fraction of Occupied Channels

When the fraction of occupied channels and the number of CR users are varied dynamically, we observe the variation in data gathering and processing time in Figures

6 and 7. The time consumed increases as the number CR users goes up, since more users request to send their measurements packet to the BS via CCC. The BS also needs more time to conduct the spectrum detection with the increasing of the measuring matrix dimensions (caused directly by increasing K, the number of CR users). However, the performance of CR-VNET is not adversely impacted, as the number of vehicles increasing since the processing at each CR user is still efficient.

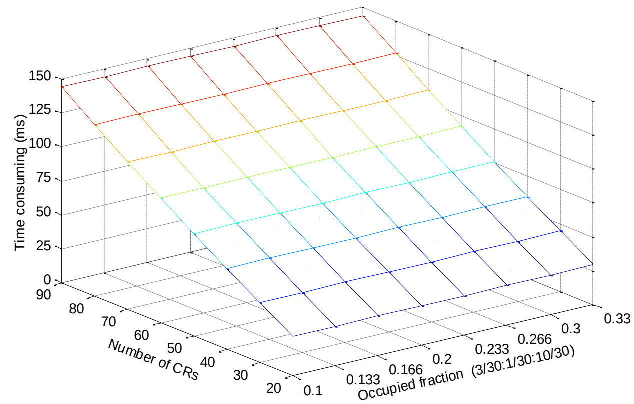

Figure 6. Time Consuming of Proposed Scheme under Different CR Numbers and Fraction of Occupied Channels

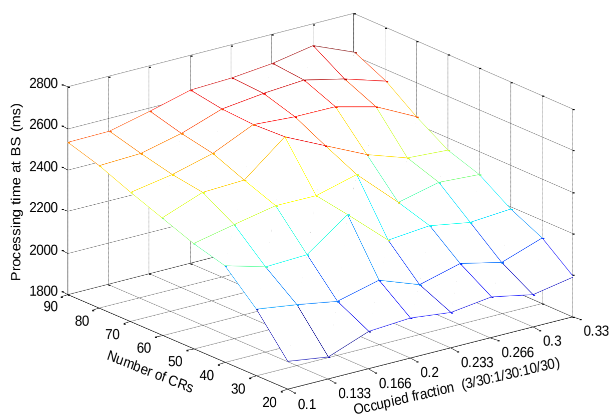

Figure 7. Processing Time of Proposed Scheme under Different CR Numbers and Fraction of Occupied Channels

5. Conclusion

In this work, we have proposed a scheme that allows vehicle based CR users to cooperatively sense the wideband PU frequencies using compressive sampling. This reduces the need for successively tuning the radio to individual channels for sensing, and also reduces the sampling rate in CR-VNETs. Each CR user only undertakes a limited computation, equivalent to computing a single matrix element, and trading off detection speed required for moving vehicles with back-end processing at the BS. Compared with the previous techniques used in classical cooperative sensing schemes, our approach reveals about 95% improvements in detection time and similar detection accuracy to optimal sensing scheme, making it suitable for CR-VNETs.

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