TECSS: Time-Efficient Compressive Spectrum Sensing Based on Structurally Random Matrix in Cognitive Radio Networks

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Abstract. As an advanced technology of implementing wideband spectrum sensing and enhancing the ability of secondary users to utilize multichannel diversity in cognitive radio networks, compressive sensing, without requirement of increasing ADC sampling rate, makes use of unique trait of sparse channel occupancy in cognitive radio networks to detect appearance of primary users in wide spectrum. However, current existing research works aim at highly accurate sensing based on Gaussian Random Matrix (GRM) design, but they fail to take time-efficient sensing into consideration, because GRM causes large computing volume and inefficiency, which lowers the capability of compressive sensing to quickly adapt to channel occupancy change rate of primary users and in turn decreases utility of spectrum exploitation for secondary users. In this paper, we design a Structurally Random Matrix (SRM) by combining GRM and Partial Fourier Matrix (PFM) to improve time efficiency of compressive sensing. As SRM possesses the sensing accuracy merit of GRM and the computing efficiency merit of PFM, the proposed compressive sensing scheme TECSS largely improves time efficiency at a cost of minor sensing accuracy. Simulation results reveal that the sensing accuracy of our proposed TECSS is 92.5% in average sense, slightly below that (95%) of compressive sensing schemes based on GRM, but time-efficiency is upgraded by 100%.

Keywords: spectrum sensing, compressive sensing, cognitive radio, time-efficient, structurally random matrix.

1 Introduction

The growth of wireless technology makes wireless applications flourish in past few years, which causes a large number of wireless communication systems to crowd in limited open access spectrum bands, while the other licensed spectrum bands, according to numerous experimental studies [1], is underutilized in time, frequency, or space. In order to improve spectrum efficiency, cognitive radio is regarded as the most promising technology which enables secondary users (SUs) to access to licensed spectrum bands allocated to primary users (PUs) in an opportunistic manner.

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So spectrum sensing is a necessity of cognitive radio technology for SUs to monitor activities of PUs and obtain the opportunity to utilize fallow spectrum bands. So, spectrum sensing plays a key role in improving spectrum efficiency in cognitive radio networks constituted by SUs.

Wideband sensing is a kind of spectrum sensing [2], which enables SUs to get the status of multiple channels parallel. Wideband sensing is more powerful to conduct SUs to acquire the gain of multichannel diversity, because SUs can choose the best available channel from a sensing result for transmission, while it is impossible in narrow-band sensing. According to Nyquist sampling theory, wideband sensing requires high sampling rate. That is, the wider the spectrum band is sensed at a time, the higher the sampling rate is required. However, linear increase in sampling rate will cause exponential increase in technologic complexity, which limits the capability of wideband sensing [3].

Compressive sensing theory was proposed by Tao and Candès[4,5], and its principium is based on sparse matrix recoverability. According to compressive sensing theory [4], if signal has a sparse representation in some other domain by transformation from time domain, it can be sampled at sub-Nyquist rate and recovered via feasible algorithms without losing any information. The sensing performance (e.g. sensing accuracy and sensing time-efficiency) is dominated by compressive matrix [5], which must be incoherent with the sparse representation basis matrix. Consequently, compressive sensing provides a method to implement wideband sensing without stringent requirement on corresponding sampling rate, which relaxes high requirement on sampling rate of A/D Convertor. As PUs intermittently occupy licensed bands, their appearance presents sparsity in frequency domain[6], which inspires researchers with large potential of compressive sensing application in wideband spectrum sensing for cognitive radio networks[7]. However, all these existing works emphasize on performance of sensing accuracy by GRM design, but they ignore performance of sensing time-efficiency. Because GRM causes large computing volume and inefficiency, their schemes are time-inefficient in recovery. Time-efficiency of compressive spectrum sensing is of importance to cognitive radio networks. On one hand, if the sensing time can be shortened, SUs will have more time to transmit data to improve aggregate throughput. On the other hand, the status of channel occupancy may transit rapidly, which requires fast sensing of SUs to adapt to activities of PUs and protect PUs from harmful interference.

In this paper, we design SRM by combining GRM and PFM. As the SRM possesses the sensing accuracy merit of GRM and the computing efficiency merit of PFM, the proposed compressive sensing scheme not only guarantees sensing accuracy, but also improves sensing time-efficiency. Our contributions of this paper include: (1) To the best of our knowledge, we are the first to take into account the time-efficiency in compressive sensing; (2) We design a novel SRM for our compressive sensing scheme to improve the sensing efficiency at the cost of minor sensing accuracy compared to those based on GRM.

The rest of the paper is organized as follows. In section 2, we overview related work of compressive sensing in cognitive radio networks. We present our designed time-efficient compressive spectrum sensing (TECSS) in details in section 3 and evaluates the performance of TECSS by simulation in section 4. Finally, section 5 concludes our work.

2 Related Work

Most of the studies of compressive spectrum sensing in cognitive radio networks focus on the sensing accuracy, but fail to concentrate on sensing time-efficiency. Secondary users must sense the spectrum environment accuracy so as to access the spectrum without interfering primary users. Resulted from its high sensing accuracy, Gaussian random matrix is widely used for compressive spectrum sensing in [6, 7]. Its incoherence with other orthogonal matrices makes the compressive sensing accurately with minimal number of measurements [5]. But because of its randomicity it has two defects: huge memory buffering and high computational complexity. In wideband compressive sensing, the number of sub-channel will be very large, so we have to choose another matrix which can be used to deal with large scale data. Moreover, we want to get TECSS, the chosen matrix must have low computational complexity.

Partial Fourier matrix in [8] is a kind of compressive matrix that exploits the algorithm of FFT so as to speed up compressive sensing. Partial Fourier matrix can significantly reduce the complexity of the compressive sampling system. However, it is only inefficient with the signals which are sparse in time-domain, thus it can't be employed in compressive spectrum sensing because the signals are sparse in frequency domain not sparse in time domain in cognitive radio networks.

In this paper, we combine the random Gaussian matrix and partial Fourier matrix to get a kind of sensing matrix called structurally random matrix to sense the spectrum time-efficiently and accurately. So far we have not found any work on sensing time-efficiency, and this missing part is exactly what we are going to do in this paper.

3 TECSS with SRM

In this section we derive secondary users with SRM sense the state transition of primary users accurately and time-efficiently.

3.1 System Model

Consider a (ultra-)wide band that hosts both primary users and secondary users. Suppose that the spectrum of B Hz is divided into N non-overlapping sub-channels,. Signals transmitted by primary users are received by secondary users [9]. We use $r(t)$ to denote the received signal by secondary users in time-domain. r_t stands for the discrete version of $r(t)$ sampled at Nyquist rate, and r_f is the spectrum form of r_t .And T_{SRM} and T_{GRM} denote the sensing time of using SRM and GRM, respectively.

3.2 Sensing Processing of Secondary Users

Secondary users sense the spectrum using received signal, the signal given by

$$r(t) = r_p(t) + n(t) \tag{1}$$

where $r_p(t)$ denote signals from primary users, $n(t)$ is additive white Gaussian noise (AWGN).Take N-point FFT (Fast Fourier Transform) of the time discrete version of (2), then we have

$$r_f = r_{p,f} + n_f. \tag{2}$$

Secondary users estimate the spectrum $r_{p,f}$ so as to choose a better sub-channel from the unoccupied frequency band. Resulted from the low spectrum utilization of primary users, $r_{p,f}$ is sparse, compressive spectrum sensing can be used. In compressive spectrum sensing secondary users collect and compress time-domain signals using compressive matrix $C_{M\times N}$ (M<<N), the measurement signal can be calculated as

$$s_t = C \times r_t \tag{3}$$

where r_t is the sampled signal of $r(t)$ at Nyquist rate f_N .With compressive sampling, the sample rate decrease to $(M / N) f_N$,which relaxes the high requirement on ADC sampling rate. And we have

$$r_t = F_N^{-1} r_f \tag{4}$$

where F_N^{-1} is the N-Point IFFT matrix. Such that we have

$$s_t = CF_N^{-1} r_{p,f} + \tilde{n}_f \tag{5}$$

where $\tilde{n}_f = CF_N^{-1} n_f$ is still AWGN. Based on compressive sensing, secondary users reconstruct the spectrum $r_{p,f}$ with compressive matrix C and measurement s_t using the recovery algorithms [10]. According to (5), s_t is the sampled signal by C , so the choice of compressive matrix C is important in compressive spectrum sensing. Both sensing accuracy and sensing time-efficiency lie on C .

3.3 Structurally Random Matrix

The sensing accuracy depends on the incoherence of compressive sensing matrix C with IFFT matrix F_N^{-1} . The coherence is low when we choose GRM as sensing matrix, so the sensing accuracy of GRM is excellent. But when GRM is used in ultra-wideband compressive sensing, its buffering memory is huge and computation complexity is very high due to their completely unstructured nature.

Now wideband compressive sensing need to be accuracy and time-efficiency, in order to keep approximate sensing accuracy, the matrix needs to have the properties of GRM to guarantee the incoherence. To speed up the sensing, we can utilize the properties of partial Fourier matrix [8]. So SRM can be designed like this

$$C = \sqrt{\frac{N}{M}} DFP \cdot \tag{6}$$

$P \in R^{N \times N}$ is a random permutation matrix, which can permute the locations of elements of a vector randomly. With this matrix we can guarantee that SRM has approximate incoherence with F_N^{-1}, thus, the sensing accuracy is approximate to the GRM.

$F \in R^{N \times N}$ is an orthonormal matrix, like the partial Fourier matrix, we can use FFT matrix, DCT matrix, or WHT matrix to reduce the computation complexity. Resulted from their fast computation algorithms the compressive sensing is speeded up.

$D \in R^{M \times N}$ is a randomly downsampler. It can randomly abstract M rows of FP, which will generate stochastically independence among the deterministic rows [8]. With this matrix we can get sub-Nyquist rate measurements. Multiplying $\sqrt{\frac{N}{M}}$ is to guarantee the same power after down rate sample.

So with this design, SRM realizes the sensing accuracy of Gaussian matrix and sensing time-efficiency of Partial Fourier matrix. As a result, using the SRM as compressive matrix for spectrum sensing realizes approximate accuracy of GRM and higher time-efficiency than GRM.

4 Simulation Evaluation

In this section, we conduct simulations to verify the availability and efficiency of proposed TECSS with SRM compared with its counterparts with GRM.

4.1 Simulation Setup and Performance Metrics

In this section, we will compare the sensing performance of SRM and GRM. The assessed sensing performance includes sensing accuracy and sensing time-efficiency. The sensing accuracy is evaluated by the probability of detection and the sensing time-cost is evaluated by system time of the computer.

4.2 Sensing Accuracy of SRM and GRM

In Fig.1, Original signal denotes the spectrum which is occupied, Recovered signal 1 and 2 denote the sensing spectrum using GRM and SRM, respectively. Difference1 and 2 denote the differences between the original signal and recovered signals. We can find that the sensing accuracy with GRM is slightly better than SRM in accuracy. In Table 1, we list the sensing accuracies with different numbers of sub-channels, we can see the average accuracy of SRM is 92.5%, it only decreases by 2.5% compared with GRM(95%).

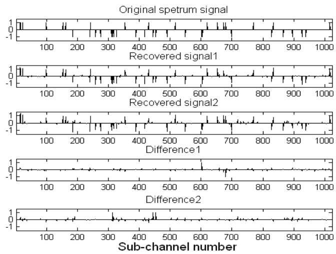

Fig. 1. the number of sub-channels is 1024, the occupied number is 40

Table 1. Sensing accuracy

Sub-channel number	GRM	SRM
500	100%	95%
1000	95%	92.5%
1500	95%	92.5%
2000	90%	90%

4.3 Sensing Time-Cost of SRM and GRM

In Fig.2, the sensing time of GRM is always longer than that of SRM. As the sub-channel numbers increase, the GRM sensing time will rapidly increases because of its high computation complexity. However, the SRM can deal with large data., the sensing time ratio is larger than 2, so the sensing speed is improved by 100% .

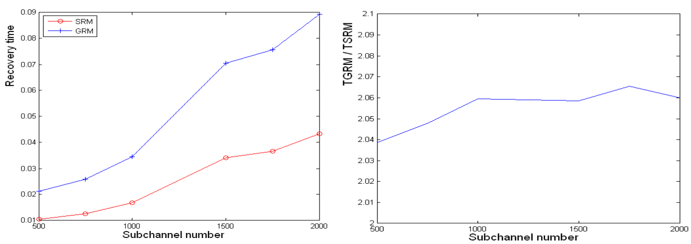

Fig. 2. Sensing time with two matrices

5 Conclusions

The former used methods of wideband compressive spectrum sensing only focused on the sensing accuracy, but failed to concentrate on the time-efficiency of sensing. Aimed at speeding up the sensing to sense fast change of spectrum and leave more time for data transmission, this paper presents TECSS based on SRM. With simulation evaluation, we verify our analysis and demonstrate the significant performance gain of TECSS with SRM. To deal with situations where primary users appear and disappear even faster, the real-time compressive spectrum sensing is our future work.

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