https://doi.org/10.59271/s44685-023-2206-3

Contents lists available at www.iusrj.org

International Uni-Scientific Research Journal

Journal homepage: www.iusrj.org

System and Signal Processing

Application of Compressive Sensing (CS) to Wide-Band Cognitive Radio signals: Tutorial.

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Article Info

Article history:

Received: 04 - 05 - 2022

Accepted: 16 - 05 - 2022

doai202205042206

Available

Vol. 4 (3) 15-22

Keywords:

compressive sensing, cognitive radio, dynamic spectrum access, restricted isometry constant.

Abstract

Compressive Sensing (CS) is a digital signal processing developed theory that encloses the signal sampling and compression, based on the sparsity characteristics of signal. This can decrease sampling rate, so reduce computational complexity of the system without degrading the performance of the system. This paper describes the theoretical frame and a few key technical, then illustrates the application of compressed sensing theory to wide-band cognitive radio signals. Spectrum sensing is a critical issue in wide-band Cognitive Radio (CR) networks as it faces hard challenges such as high hardware cost, complexity, sampling rate and processing speed. Thus, this paper shows that Compressive Sensing could be exploited in wide-band Cognitive Radio networks to solve the spectrum sensing problems mentioned above.

1.INTRODUCTION:

Digital signal processing technology and the fast improvement of digital processing devices make digital signal processing assume a basic job in signal processing. Sampling is the main route to convert from the analog signal to digital signal, and sampling theorem is a scaffold connecting the analog signal and digital signal.

To reconstruct the first analog signal without distortion, sampling theorem requests that the sampling rate to be equals or higher than twice the largest frequency in the signal. As of late, as a result of individuals' developing interest for data, the bandwidth of the signal conveying the data ends up more extensive and more extensive. Therefore, the required sampling rate and system

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processing speed prerequisites are increasingly elevated, which is the troubles in processing broadband and ultra-broadband signal. By and by, increasingly more data is required. In order to reduce the weight of storage and transmission, compression regularly is fundamental, (for example, picture compression, video compression, sound compression, and so on.). In the compression process, a number non-basic information is disposed of, while relatively small number of valuable data is held. This processing mode, from fast sampling to compression, wastes a lot of resources. In 2004, Donoho and Candes et al proposed compressed sensing (CS) theory, which is another signal acquisition and encoding and decoding theory exploiting the sparsity of signal. Compressed sensing joins the sampling and compression, which can decrease the signal sampling rate, reduce the expense of the transmission and data saving, and altogether decrease the time and expenses of processing. The compressive sensing theory demonstrates that when the signal has the property of sparsity (or compressible), the original signal can be exactly or around reproduced by the projections which sample a small part of signal. In the theoretical approach, the sampling rate is not measured by the signal bandwidth, and determined by the structure of data of the signal. Thus, signal sampling and compression can be done simultaneously at low speed, which can enormously decrease the expense of sensor sampling and computation [1,2,3].

CS can be utilized in identifying and estimating sparse physical signals, for example, MIMO signals, wide-band cognitive radio (CR) signals, and ultra-wide-band (UWB) signals, and so on. In this paper, we highlight the utilization of compressed sensing theory in wide-band cognitive radio (CR) signals as a spectrum sensing approach.

The reminder of this paper is organized as follows: Section 2 introduces the main principle of compressed sensing theory. In section 3, we summarize the main idea of cognitive radio networks (CRN). Finally, Section 4 presents the application of the compressed sensing theory to wide-band cognitive radio signals, and we conclude in Section 5.

COMPRESSIVE SENSING (CS) THEORTICAL BACKGROUND

In light of the sparsity of signal (or sparse in a transformation domain), compressed sensing theory extends the high-dimensional signal on a lower dimensional space utilizing measurement matrix which isn't relevant to transformation base, and afterward reproduces the original signal with high likelihood using a small number of projections through solving an optimization problem. The procedure of compression and reconstruction of signal with compressive sensing is depicted in Figure 1.

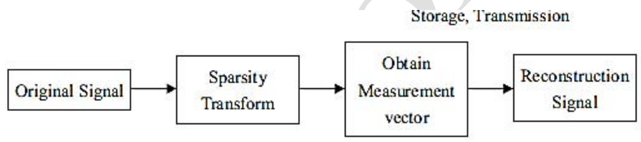

Fig. 1 Diagram of compressed sensing

Fig. 1 illustrates the three main stages of compressive sensing, which are sparsity transform, obtain the measurement vector form the measurement matrix, and finally the recovery (reconstruction) of the original signal. In the sparsity transform stage [4], a sparse representation of the signal is found over a premise that permits to recover the signal as precisely as possible. In the following stage, the sparse signal is sampled and compressed dependent on a measurement's matrix [5,6,7]. In the last stage, the compressed signal is then recovered using a reconstruction algorithm [8,9,10,11].

Considering a high dimensional signal x with a large number of samples N, x is thought to be sparse in some space, and it is k-sparse signal with $k << N$. Sparse representation comprises of representing the signal by various projections on a appropriate sparse basis φ, otherwise called dictionary or projection. Instances of sparse basis incorporate wavelet transform, Fourier transform, and discrete cosine transform. Non sparse signal can be expressed to as a sparse signal by some sparse transforms. Each sparse signal can be expressed to in a scarifying basis φ as follows

$$X = \varphi * S \qquad (1)$$

where s is the signal's projection on the sparse basis φ ($N * N$), and $||s||0 = k \ll N$ [12, 13]. The sparse signal x is compressed utilizing the measurement matrix Φ. The compression is based on multiplying the signal with a M * N matrix. M is a lot littler than N and it expresses to the measurements number that contains the fundamental information of x. For effective reconstruction, M should regard this condition M = O (k log (N)). The compressed signal is given by

$$y = \Phi * X \qquad (2)$$

where y (M, 1) is the signal measurements, which takes only M samples from x (N, 1), M << N. Φ is the measurement matrix (M, N) as shown in Figure 2

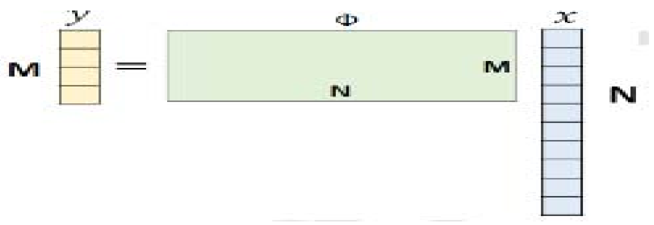

Fig. 2 Measurement vector structure

From equations (1) and (2), compressed signal can be expressed as

$$y = \Phi * X = A * S \qquad (3)$$

where A = φ ∗ Φ is a M * N matrix, referred as recovery matrix, it fulfills the restricted isometry property. The last step comprises of reproducing the signal at the receiver, implied solving the equation (3). It plans to solve an undetermined system with a greater number of unknowns than the number of equations. In view of the sparsity assumption, it is conceivable to estimate a high dimensional signal N from small number of measurements M. To solve the undetermined system and approximate x coefficients, the problem is looked as an optimization problem. Different reconstruction algorithms have been created to solve the following optimization problem

$$\tilde{x} = \arg\min_{y=\Phi x} \|x\|_1 \quad \text{Subject to} \quad y = \Phi * x \qquad (4)$$

where the reconstructed signal is the sparsest solution from many possible solutions of the optimization problem. ||x||1= ∑i|xi| is the $\mathcal{L}1$ norm of x and represents the sum of the absolute values of

x coefficients $\|X\|_m = \sqrt[m]{\sum_i |x_i|^m}$ is the $\mathcal{L}_m$ norm [10, 14].

Considering noise, two cases are raised, noisy case and noiseless case. In useful applications, a random noise is added to the calculated measurements during the signal processing. Thus, with the noisy measurements, equation (2) can be expressed as

$$y = \Phi * X + e \qquad (5)$$

where e is a random noise vector that should be assessed during the reconstruction procedure. Considering the noise, the optimization problem can be reformulated as

$$\tilde{x} = \arg\min_{y=\Phi x+e} \|x\|_1 \quad \text{Subject to} \quad y = \Phi * x \qquad (6)$$

Various recovery algorithms have been proposed to solve the linear programming problem, for example, $\mathcal{L}1$ norm minimization, gradient descent, iterative thresholding, matching pursuit, and orthogonal matching pursuit [7, 8, 15,16,17,18,19]. Example of techniques that recovers the original signal with noise is described in [20]. For efficient compressive sensing, a few necessities and presumptions ought to be considered before processing. Determining the sampling matrix to use for compression and which solver to apply rely upon certain conditions including sparsity, restrict isometry property, coherence, and measurements number.

Sparse signal is a signal with a small number of non-zero components and most components are zero or with extremely low power. A signal with N samples is k-sparse implies that it has just k non-zero coefficients and (N - k) zero components, where N is larger than k. Sparse representation is an important necessity for compressive sensing, it guarantees the signal compressibility. It is based on representing the signal in some domain with only essential information obtained. The restricted isometry property is a property that describes orthonormal matrices. A matrix that fulfills this property in order k indicates that.

$$\exists \delta \in (0,1) / (1-\delta)\|x\|_2^2 \le \|\Phi x\|_2^2 \le (1+\delta)\|x\|_2^2 \qquad (7)$$

where δ is the restricted isometry constant (RIC) [6]. This property permits to ensure the uniqueness of the reconstructed solution, and it must be considered during the matrix design. At the point when a matrix fulfills the restricted isometry property, it ensures that the undetermined system solution is unique.

and robust. Fourier, random Gaussian, and Bernoulli matrices are instances of matrices that fulfill the restricted isometry property [21]. For coherence property, it looks at the sensing matrix quality and assesses its efficiency. Mutual coherence of two matrices Φ and φ measures the maximal correlation between's any two components of them, μ (Φ, φ) is figured as

$$\mu(\Phi,\varphi)=\sqrt{N}\max_{1\le i,j\le N}\left|\left\langle \Phi_i \middle| \varphi_j\right\rangle\right| \tag{8}$$

where 1 < μ(Φ, φ) < . High coherence is proportionate to high correlation among's Φ and φ components, which indicates that the compressive sensing procedure needs more measurements. Compressive sensing requires that Φ is incoherent with φ. The small value of coherence implies few measurements are required for signal recovery. The coherence of the sensing matrix can be characterized likewise as μ(φ), which represents the largest value of correlation between's any two normalized columns of Φ, μ(φ) is given as

$$\mu(\Phi)=\max_{1\le i\ne j\le N}\left|\left\langle \Phi_i \middle| \varphi_j\right\rangle\right| \tag{9}$$

where Φi and Φj are two columns of Φ. The smaller number of measurements requires the lower value of coherence [6].

Cognitive Radio Networks (CRN)

Radio frequency (RF) spectrum is an important yet promptly controlled resource because of its extraordinary and significant function in wireless communications. With the expansion of wireless services, the needs for the RF spectrum are continually expanding, which leads to scarce spectrum resources. Then again, it has been informed that localized temporal and geographic spectrum use is very low [27]. Right now, new spectrum policies are being created by the Federal Communications Commission (FCC) that will enable secondary users to opportunistically use the licensed band, when the primary user (PU) is idle. Cognitive radio [28], [29] has turned into a promising technology to overcome the spectrum scarcity issue in the next generation cellular networks by utilizing opportunities in frequency, time, and space domains.

Cognitive radio is an advanced software-defined radio that consequently senses its surrounding RF environment and cleverly adjusts its operating parameters to network infrastructure while fulfilling user needs. Since cognitive radios are considered as secondary users for utilizing the licensed band, a critical necessity of cognitive radio systems is that they should productively take advantage of under-utilized spectrum (signified as spectral opportunities) without leading to hurtful interference to the PUs. Moreover, PUs has no commitment to share and change their operating parameters for sharing spectrum to cognitive radio systems. Consequently, cognitive radios ought to have the option to autonomously detect spectral opportunities with no help from PUs; this ability is called spectrum sensing, which is considered as one of the most basic parts in cognitive radio systems.

Application of compressive sensing to wide-band cognitive radio signals

Dynamic spectrum access (DSA) is a new approach to solve today's radio spectrum scarcity problem. Key to DSA is the cognitive radio (CR) that can sense the environment and adjust its transmitting parameters accordingly to not cause interference to other primary users of the frequency. Thus, spectrum sensing is a critical function of CR [30,31]. However, wide- band spectrum sensing faces hard challenges. There are two main approaches used for wide-band spectrum sensing. First, we can use a bank of tunable narrow-band filters to search narrow-bands one by one. The challenge with this approach is that a large number of filters need to be used, leading to high hardware cost and complexity. Second, we can utilize a single RF front-end and use DSP to explore the narrow-bands. The challenge in this approach is that extremely high sampling rate and processing speed are required for wide-band signals. CS can be utilized to surpass the challenges referenced previously. Today, a little bit of the wireless spectrum is intensely utilized while the rest is incompletely or seldom utilized. In this way, the range signal is inadequate and CS is pertinent. In this section, we present three approaches of applying CS spectrum sensing problem.

Spectrum Sensing (Digital Approach)

It is a digital approach in which the signal is first converted to the digital domain, and then CS is performed on the digital signal. Let x(t) signify the signal sensed by CR, B the frequency range of the wide-band, F the group of frequency bands presently utilized by other users. Typically, [22], showing that x(t) is sparse in the frequency domain and therefore CS is usable. In this way, rather than sampling at Nyquist rate fN , we can sample at a much slower rate generally around . In [23], the CS formulation of spectrum sensing was proposed as

$$f = \arg\min_{f} \|f\|_1 \quad \text{Subject to} \quad x_t = Sx(t) = SF^{-1}f \qquad (10)$$

where f is signal representation in the frequency domain, is the inverse Fourier transformation, and S is a reduced-rate sampling matrix operating at a rate close to , and is the reduced rate measurement. Simulation results in figure 3 show that good signal recovery can be achieved at 50% Nyquist rate [23].

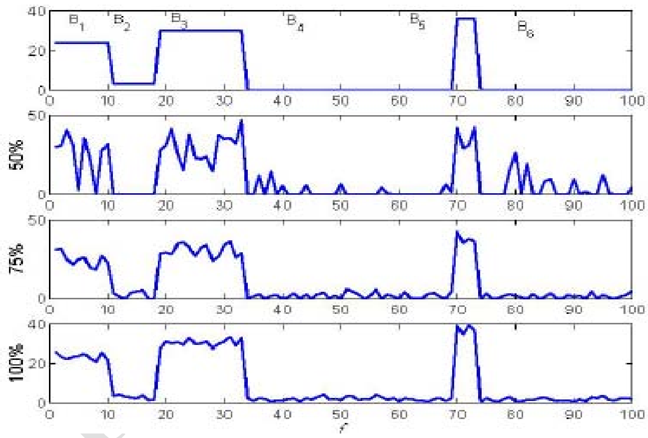

Fig. 3 signal frequency response: (top) noise-free signal; (rest) recovered signal at compressing ratios = 50%, 75%, 1. Spectrum Sensing (Analog Approach)

In this approach, CS is straightforwardly performed on the analog signal [24], which has the upside of saving the ADC resources, particularly in situations where the sampling rate is high. A parallel bank of filters is utilized to get measurements yi. To decrease the number of filters required, which is equivalent to the number of measurements M and can be possibly enormous, each filter samples time-windowed portions of signal. Let NF referred to the number of filters required, and NS signify the number of segments each filter gets. For whatever length of time that NFNS = M, the measurement is adequate. Simulations were performed for an OFDM-based CR system with 256 sub-carriers where just 10 carriers only are simultaneously active. The results in figure 4 demonstrated that a CS system with 8-10 filters can perform spectrum sensing at 20/256 of the Nyquist rate [24].

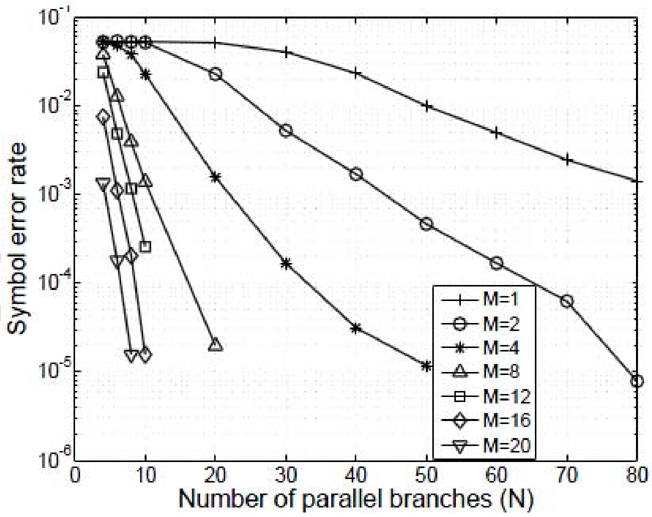

Fig. 4 Symbol error rate with different number of segments where M=NS. Spectrum Sensing (Cooperative Approach)

The performance of CS-based spectrum sensing can be adversely affected by the channel fading and the noise. To surpass such problems, a cooperative spectrum sensing scheme dependent on CS was proposed in [25]. In this scheme, the suspicions are that there are J CRs and I active primary users. The whole frequency range is separated into F non-overlapping narrow-bands . In the sensing period, all CRs stay silent and cooperatively perform spectrum sensing. The signal received at jth CR is

$$x_j(t) = \sum_{i=1}^{I} h_{i,j}(t) * s_i(t) + n_j(t) \qquad (11)$$

where hi,j is the channel impulse response, si(t) is the signal transmitted from primary user i, * signifies convolution, and nj(t) referred to noise at the receiver j. After taking discrete Fourier transform on xj(t) we obtain

$$\tilde{x}_j(f) = \sum_{i=1}^{I} \tilde{h}_{i,j}(f) * \tilde{s}_i(f) + \tilde{n}_j(f) \quad (12)$$

In this scheme, spectrum detection is applicable even-though when the channel impulse responses are unknown. If, then some primary user is utilizing the channel except if the channel experiences deep fades. Since it is impossible that all the CR experience deep fades simultaneously, cooperative spectrum sensing is substantially more powerful than individual sensing. Cooperative spectrum sensing is completed in two stages. In the initial step, compressed spectrum sensing is done at every individual CR utilizing the approach in [23]. Moreover, the jth CR keeps up a double F -dimensional occupation vector uj, where uj,i = 1 if the frequency band is detected to be occupied and uj = 0 otherwise. Secondly, CRs in the one-hop neighbourhood exchange the occupation vectors and afterward update their own occupation vectors utilizing the method of average consensus [26] as pursues

$$u_j(t+1) = u_j(t) + \sum_{k \in N_j} w_{j,k}(u_k(t) - u_j(t)) \quad (13)$$

where Nj is the neighbourhood of jth CR, and wj,k is the weight related with edge (j, k), the selection rules of which are portrayed in [26]. With appropriate selection rules, it can be demonstrated that

$$\lim_{t \to \infty} u_j(t) = \frac{1}{J} \sum_{k=1}^{J} u_k(0) \quad (14)$$

That is, the frequency occupation vectors of the CRs in the neighbourhood all reach the same value that is the average of their initial values. The jth CR can decide the frequency band i is occupied if , or a majority rule can be used, i.e., the frequency band i is considered occupied

if . Simulation

Results in figure 5 showed that the spectrum sensing performance improves with the number of CRs involved in the cooperative sensing and the average consensus converges fast (in a few iterations) [23].

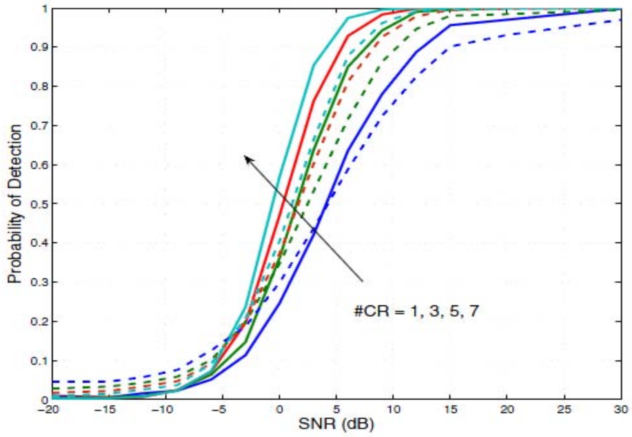

Fig. 5 Probability of detection for various number of collaborating CRs,

for Pfa = 0.01. Solid lines: no compression; dash lines: compression at K/M = 50%.

Conclusion

Compressed sensing theory joins the progress of signal sampling and compressing dependent on the sparsity of signal, which can decrease sampling rate. The paper gives a general depiction about Compressed sensing theory, and spotlight on the utilization of compressed sensing theory to wide-band cognitive radio signals, which just exploits CS to sense the spectrum in CR networks. The most effective approach to decrease the sensing time in spectrum sensing process is focal point of future study.

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