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A survey on compressive sensing techniques for cognitive radio networks

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ABSTRACT

In cognitive radio, one of the main challenges is wideband spectrum sensing. Existing spectrum sensing techniques are based on a set of observations sampled by an analog/digital converter (ADC) at the Nyquist rate. However, those techniques can sense only one band at a time because of the hardware limitations on sampling rate. In addition, in order to sense a wideband spectrum, the band is divided into narrow bands or multiple frequency bands. Secondary users (SU) have to sense each band using multiple RF frontends simultaneously, which results in a very high processing time, hardware cost, and computational complexity. In order to overcome this problem, the signal sampling should be as fast as possible, even with high dimensional signals. Compressive sensing has been proposed as one of the solutions to reduce the processing time and accelerate the scanning process. It allows reducing the number of samples required for high dimensional signal acquisition while keeping the important information. Over the last decade, a number of papers related to compressive sensing techniques have been published. However, most of these papers describe techniques corresponding to one process either sparse representation, sensing matrix, or recovery. This paper provides an in depth survey on compressive sensing techniques and classifies these techniques according to which process they target, namely, sparse representation, sensing matrix, or recovery algorithms. It also discusses examples of potential applications of these techniques including in spectrum sensing, channel estimation, and multiple-input multiple-output (MIMO) based cognitive radio. Metrics to evaluate the efficiencies of existing compressive sensing techniques are provided as well as the benefits and challenges in the context of cognitive radio networks.

1. Introduction

Over the last decade, a number of spectrum sensing techniques have been proposed to detect and locate dynamically unused spectrum channels in a band of interest [1–6]. Examples of these techniques include energy detection [7], matched filter [8], autocorrelation [9–11], and wavelet based detection [12]. Energy detection operates by comparing the SU signal average energy with an estimated threshold. This technique does not require any knowledge of the PU signal and it is simple and easy to implement. However, it has high false detection rates and it is not able to distinguish between signals and noise [7]. Matched filter requires the knowledge of the PU signal characteristics including frequency, modulation type, and bandwidth. It operates by comparing the matched filter output with a threshold [8]. Autocorrelation based detection requires

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the knowledge of the statistical distribution of the autocorrelation function. It operates by comparing the autocorrelation function at lag 0 with that at lag 1. This technique is able to differentiate between signals and noise, which makes it less sensible to noise uncertainty [9–12]. Wavelet based sensing is based on wavelet transform to detect the singularities of the power spectral density (PSD). It works by computing the wavelet transform of the SU signal and calculating PSD, which is then compared to a threshold to make the decision about the signal presence. This technique does not require the knowledge of the PU signal; however, it requires the mother wavelet to be chosen appropriately in order to operate efficiently [13].

The above sensing techniques, also called non-compressive sensing detectors, are based on a set of observations sampled by an analog/digital converter ADC at the Nyquist rate [14]. However, these techniques can sense only one band at a time because of the hardware limitations on sampling rate. In addition, in order to sense a wideband spectrum, the band is divided into narrow bands or multiple frequency channels. The SU has to sense each band using multiple RF frontends simultaneously, which can result in a very high processing time, hardware cost, and computational complexity. To overcome some of these limitations, compressive sensing has been proposed as one of the solutions to reduce the processing time and accelerate the scanning process. It allows reducing the number of samples required for high dimensional signal acquisition while keeping the important information [15–17].

In compressive sensing theory, a signal can be acquired and compressed simultaneously in the same process with only the essential information. The signal can be then recovered from few measurements at the Nyquist rate or less. Compressive sensing can be achieved by respecting certain requirements, including sparsity, restrict isometry property (RIP), and incoherence. This approach has been applied in several domains, in which it offered good results over the conventional approaches. Examples of these domains are radar systems [18], medical systems for rapid magnetic resonance imaging (IRM) [19,20], and wireless sensor networks for signal acquisition [21]. In cognitive radio, this approach is also applicable because of the signal sparsity feature, which is valid in most of spectrum sensing scenarios.

Compressive sensing was also applied on channel estimation to overcome the limitations of the existing channel estimation techniques, known as non-compressive sensing channel estimation techniques. A number of these techniques have been proposed in the literature to evaluate and approximate the channel behavior [22–27]. Examples of these techniques include pilot-aided [22–24], blind [25], and least mean square (LMS) based channel estimation [26]. The channel estimation pilot aided techniques include a number of schemes such as minimum mean squared error (MMSE) and maximum likelihood estimator (MLE) based technique [22–24]. In [23], a low rank estimation technique based on MMSE has been proposed for estimating channel pilots using singular value decomposition. This technique requires the SNR and channel frequency correlation to be known. In [24], the MLE was used for channel estimation in the context of OFDM-MIMO. Unlike the MMSE based method, this technique does not require the knowledge of the channel information or SNR to operate. The blind channel estimation technique consists on using the data symbols to estimate the parameters of the channel. This technique is not efficient for fading channels and represents high complexity [25]. LMS based channel estimation represents low complexity compared to the other techniques and it consists on computing the LMS based on the transmitted signal over the channel and the identity matrix [26].

The aforementioned techniques represent high complexity and often require the knowledge of the channel response at the receiver for multipath wireless channels, which is not always possible in practice because of the high number of required antennas [22–26]. Moreover, multichannel signals are known to be sparse, which can lead to high estimation errors at the receiver. In order to overcome these limitations and exploit the sparsity of the multipath wireless channels, compressive sensing channel estimation techniques have been proposed and investigated, especially for MIMO–OFDM communication systems [27].

A number of papers and surveys related to compressive sensing have been published. However, most of these papers describe compressive sensing techniques corresponding to one process either sparse representation, sensing matrix, or recovery. Other papers focus on one of the compressive sensing category; and a few focus on the compressive sensing applications. Thus, there is a need for detailed review papers that compare and analyze the current compressive sensing techniques. Therefore, this paper provides a detailed overview on compressive sensing techniques and classifies these techniques according to which process they target, namely, sparse representation, sensing matrix, or recovery algorithms. The paper also discusses each category, some techniques under each category, and provides a comparison of these categories. In addition, examples of compressive sensing applications in cognitive radio networks, MIMO, and channel estimation, are discussed.

In this paper, we present a detailed overview of compressive sensing techniques and their applications in cognitive radio systems. The rest of this paper is organized as follows. Section 2 presents the compressive sensing model and its requirements. Section 3 reviews the sensing techniques classification, which is based on the involved process. Section 4 presents compressive sensing potential applications in conventional and MIMO cognitive radio contexts. Subsequently, it also discusses compressive sensing limitations and tradeoffs involved in selecting which compressive sensing scheme to adopt. Finally, a conclusion is given at the end.

2. Compressive sensing theory

The concept of compressive sensing is introduced by Candes as a new approach to sample signals at or below the Nyquist rate [28,29]. Traditional approaches were based on Shannon–Nyquist theorem, in which it is possible to recover a signal at the receiver only if it is sampled at the Nyquist rate.