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Theoretical stopping criteria guided Greedy Algorithm for Compressive Cooperative Spectrum Sensing

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ABSTRACT

Cooperative spectrum sensing (CSS) in homogeneous cognitive radio networks conducts cooperation among sensing users to jointly sense the information of spectrum usage for recovery of spectrum status and utilization of available ones. Motivated by the fact that the number of occupied channels is sparse, the mechanism of greedy multiple measurement vectors (MMVs) in the context of compressive/compressed sensing can ideally model the wideband CSS scenario to efficiently solve the support detection problem for identification of occupied channels. Actually, the number of sparsity is unknown, and the existing greedy algorithms for MMVs lack for a robust stopping criterion of determining when the greedy algorithm should terminate. In this paper, we analyze and derive oracle stopping bounds that are independent of prior information such as sparsity for greedy algorithms. Simulations are provided to confirm that, in compressive cooperative spectrum sensing, the proposed stopping criteria for greedy algorithms can remarkably improve detection performance.

1. Introduction

1.1. Background

Cognitive radio [1] is one of solutions to efficiently solve sparse spectrum usage [2] in wireless communications in that Secondary Users (SUs) are allowed to sufficiently exploit available spectrums, which are not currently used by Primary Users (PUs), via spectrum sensing (SS) techniques. Most existing methods, based on Nyquist sampling for the purpose of exact recovery of the original signal, require large sampling rates under wideband spectrum sensing scenarios [3].

With an eye on the fact [2] that only few spectra will be used, *i.e.*, only few PUs are active, such characteristic of sparsity meets the assumption of compressed sensing (CS) [4–6], which is a revolutionary sampling theory that has received considerable attention recently in achieving the sub-Nyquist rate sampling.

Moreover, in wireless communications, the transmitted signals easily suffer from fading and noise interference. Fortunately, with cooperative spectrum sensing (CSS), all cooperative SUs can jointly sense the spectrums to better detect the status of spectrum usage [7–9] from the sensed signals. Since the SUs in CSS share the same sparsity pattern for spectrum detection, joint sparsity model (JSM) [10] is suitable to model CSS.

In the literature, there exist some solutions to JSM. In this paper, we particularly focus on the solver, called *Multiple Measurement Vectors* (MMVs) [11,12], which are composed of more than one measurement vector in the context of compressed sensing. MMVs accommodate the scenario of CCS in that more than one SUs are deployed. Moreover, CSS mainly cares about whether a channel is used or not, leading to the support detection problem. In other words, the number of active PUs in CSS corresponds to that of supports in CS.

In the context of compressive sensing, the sparse signal recovery or support detection from (far) fewer measurements can be achieved in two ways: matching pursuit (MP) and convex optimization (*e.g.*, ℓ_1-optimization). In the CSS literature, ℓ_1-optimization is employed in [7,8], incurring high complexity to delay and void the detection results. In contrast with ℓ_1-optimization, orthogonal matching pursuit (OMP) [13] is considered as a good solver due to its efficiency and computation simplicity. Although OMP is efficient, its recovery performance will be degraded due to the effect of fading and noise interference.

A crucial step in OMP is the stopping criterion that will affect its recovery performance. One popular stopping criterion for OMP is set to be the sparsity K of a signal in that if K supports are detected, then OMP stops its greedy iterations. The sparsity of a signal, however, is usually unknown in advance. This is also the case

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in CSS. As far as we know, the study of stopping criteria for OMP under the scenario of MMVs with unknown sparsity is still relatively unexplored in the literature.

As for MMV solvers, SOMP (Simultaneous Orthogonal Matching Pursuit)[[14] is considered to be a basic algorithm extended from OMP to MMVs. In [15], an advanced greedy algorithm, called Rank-Awareness Order Recursive Matching Pursuit (RA-ORMP), is proposed to deal with sparse signal recovery from MMVs, but without taking noisy measurements into account. In [9], Distributed OMP (DOMP) is presented to process measurement vectors in a distributed manner. Moreover, [16] proposes five thresholding-based algorithms for joint sparse recovery; however, most of thresholds are designed to be related to sparsity K, which is, however, unknown in advance.

1.2. Related work

CSS is a key technique to achieve better performance of spectrum sensing when channel fading or shadowing occurs. According to the sensing range of spectrum, spectrum sensing can be divided into two categories: narrowband sensing and wideband sensing. In narrowband CSS, [17] introduces machine learning techniques, including supervised and unsupervised learning, to model active PUs among channels while [18] conducts energy detection under Nyquist sampling rate to judge if a PU is active with the detection results being generated for further machine learning analysis. Although CSS using machine learning in [17] can provide reliable results, it takes much time cost for SUs to build a classifier. Evidently, this is not an efficient process for wideband spectrum sensing. In [19]. the authors introduce a mechanism to decide sensing nodes and optimal energy detection threshold for cooperative spectrum sensing with energy saving. In addition to energy detection, traditional narrowband sensing also includes matched filtering detection [20] and cyclostationary feature detection [20], which was applied on CSS [21].

For the purpose of providing efficient spectrum sensing, wideband spectrum sensing is a more powerful solution than narrowband sensing. Generally, wideband sensing can be divided into two categories: Nyquist sensing and sub-Nyquist sensing [22]. As for Nyquist wideband sensing, [23] proposes a multiband joint detection algorithm by using standard analog-to-digital converter; [24] makes use of wavelets to design a spectrum sensing algorithm; and a filter bank spectrum sensing algorithm is proposed in [25]. Since wideband sensing covers a very large range, a higher sampling rate will incur higher computational overhead. For this, sub-Nyquist sensing is an alternative to considerably reduce sampling cost.

To solve the critical problem of sub-Nyquist sensing, the core of compressive sensing, beyond Nyquist sampling rate, has received much attention for spectrum sensing [7,8,26].

Tian and Giannakis [27] first used CS in wideband spectrum sensing. They further enhance the robustness against noises in [28]. However, their method requires that the sparsity level should be known in advance. In [29], Wang *et al*. provided a two-step compressive spectrum sensing (TS-CSS) algorithm that can be solved at low sampling cost. TS-CSS changes the sampling rates based on sparsity level of spectrum adaptively. However, TS-CSS needs the sparsity level estimation, leading to extra computational overheads. Sun *et al*. [30] proposed an algorithm that can avoid sparsity level estimation and adjust the sampling rate adaptively at the expense of needing an iterative process with higher computational complexity. In [31], Qin *et al*. utilized geolocation database to estimate the sparsity level as prior information for signal recovery. Moreover, by observing the fact that sparsity implies low-rank, Qin *et al*. exploited low-rank completion to present a two-phase algorithm in [32]. Different from the above works, we explore the energy of noises to avoid sparsity level estimation in our method.

On the other hand, several methods [33–36] have been proposed to solve the CSS problem based on CS but focusing on the issues different from the ones in the aforementioned methods. Specifically, in order to decrease complexity at each sensing node in wideband cooperative CSS, a so-called Distributed Sensing Matrix (DSM) algorithm based on CS was developed by Farrag *et al* [33]. To further lower computational overheads and enhance reconstruction accuracy on wideband detection, Zhao *et al*. made use of CS with sequential detection to construct an integrated framework in [34]. In addition, the cooperative spectrum sensing schemes presented in [35,36] can simultaneously guarantee the performance and reduce the energy consumption in signal acquistion, processing, and transmission based on exploiting the co-sparsity among SUs.

1.3. Contributions

In this paper, we aim to study a practical subspace MMVs algorithm for CSS by presenting robust stopping criteria. Since noise interference will unavoidably make some supports un-detected, we mainly aim to detect those significant ones without necessarily recovering all. Specifically, we derive theoretical bounds as the stopping rules in a noisy MMVs environment to deal with noisy measurements. The derived bounds are simply constrained by the noise variance and measurement matrix's dimensionality, and are verified to be effective via simulations and comparisons.

In addition to stopping criteria, it is crucial in both theoretical and practical aspects to explore the upper bound of number of measurements used in compressive sensing and the upper bound of distance between a pair of primary user and secondary user in the scenario of spectrum sensing. As for measurements, a large amount of measurements will be beneficial to signal recovery but will incur communication overhead and waste of sensing energy. Hence, the use of proper amount of measurements is of paramount importance in the framework of compressive sensing-based cooperative spectrum sensing. As for the distance between a pair of primary user and secondary user, if second users are not properly deployed, the sensing signals will be weakened to affect the detection capability. The aforementioned two issues will be seriously treated in the paper.

Finally, our proposed stopping criteria are readily incorporated into the existing subspace-based MMVs algorithm to improve their support detection performance. In the literature, subspace-based algorithms [37,38] have been applied to MMVs. Especially, [37] improves [38] to maintain detection quality with less measurement vectors when noise interference exists. In [39], we have modified [37] to adapt to our stopping criteria without needing to use the prior knowledge regarding sparsity. However, in this paper, the theoretical analyses are entirely explored. The derived stopping criteria, in fact, are able to overcome the realistic problem of unknown sparsity while maintaining good support detection rate. It also deserves to note that our stopping criteria can be adaptive to the existing greedy algorithms in CS in order to achieve robust sparse signal recovery or support detection.

We apply some state-of-the-art subspace-based MMVs equipped with our derived stopping criteria and upper bound of measurements to cooperative spectrum sensing in homogeneous cognitive radio networks. Simulation results are also provided to validate the feasibility of our method.

1.3.1. Comparison with our previous works [40] and [41]

For [40] and [41], we mainly address the problem of compressed sensing with multiple measurement vectors (MMVs) associated without and with prior information, respectively, in order to