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Support Recovery with Sparsely Sampled Free Random Matrices for Wideband Cognitive Radio Receiver

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ABSTRACT

The main objective of this project is to design an eigenvalue-based compressive SOE technique using asymptotic random matrix theory. In this project, investigating blind sparsity order estimation (SOE) techniques is an open research issue. To address this, this project presents an eigenvalue-based compressive SOE technique using asymptotic random matrix theory. Finally, this project propose a technique to estimate the sparsity order of the wideband spectrum with compressive measurements using the maximum eigenvalue of the measured signal's covariance matrix.

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KEYWORDS: *Compressed sensing, free probability, random matrices, rate-distortion theory, sparse models, support recovery*

I. INTRODUCTION

COGNITIVE RADIO (CR) communications is considered a promising solution in order to enhance the spectral efficiency of future wireless systems [1]. Among several CR techniques proposed in the literature, Spectrum Sensing (SS) is an important mechanism in order to acquire the spectrum awareness required by the CRs. Existing SS techniques mostly focus on the detection of narrowband signals considering a single radio channel [2]–[5]. However, in practical scenarios, the CRs need to detect and acquire information about a wide spectrum band in order to utilize the spectrum efficiently. Further, CRs do not have prior knowledge about the PU's signal and channel. In this aspect, investigating efficient blind spectrum awareness techniques is an important and relevant research challenge. The key challenge of SS is the detection of weak wideband signals hidden in thermal noise with a sufficiently large probability of detection. The sensing Radio Frequency (RF) chain of a CR receiver should be able to receive a wideband signal, sample it using a high speed Analog to Digital Converter (ADC) and perform measurements for the detection of PU signals. The wideband RF signal received by the antenna of an RF front-end includes signals from adjacent and spatially separated transmitters, and from transmitters operating at a wide range of power levels and channel bandwidths. In this context, one of the main challenges in implementing a wideband CR is the design of the RF front-end [6], [7]. Further, the main limitation in an RF front-end's ability to detect weak signals is its Dynamic Range (DR). For this purpose, the wideband sensing requires multi-GHz speed ADCs, which together with high resolution (of 12 or more bits) might be infeasible with current technology [8], [9].

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A mobile adhoc network (MANET) consists of wireless mobile devices or "nodes", such as laptops, cell phones, and Personal Digital Assistants (PDAs), which can move in the network system openly. Fig 1 shows the structure of MANET. In addition to mobility, mobile devices cooperate to forward packets to one another to extend the restricted transmission range of each node. This is achieved by multi- hop relaying, which is used in many applications, such as disaster relief, military operation, and emergency communication. Security is an important need for these network services. Provisioning secure communication between two nodes is main concern. Because of its characteristics, such as infrastructure-less, mobility and dynamic topology, MANET is vulnerable to various types of security attacks.

Among all security viewpoints in MANET, certificate management is generally used mechanism, which is utilized to secure applications and network services. Certification is a prerequisite to secure network communication. Certificate is a data structure in which public key is bound to the attributes by the digital signature of the issuer, and can be used to verify the identity of individual, and also to prevent tampering and forging in mobile ad hoc networks.

Need for Certificate Revocation: Certificate management is basically used to covey trust in public key infrastructure to secure network services and applications.

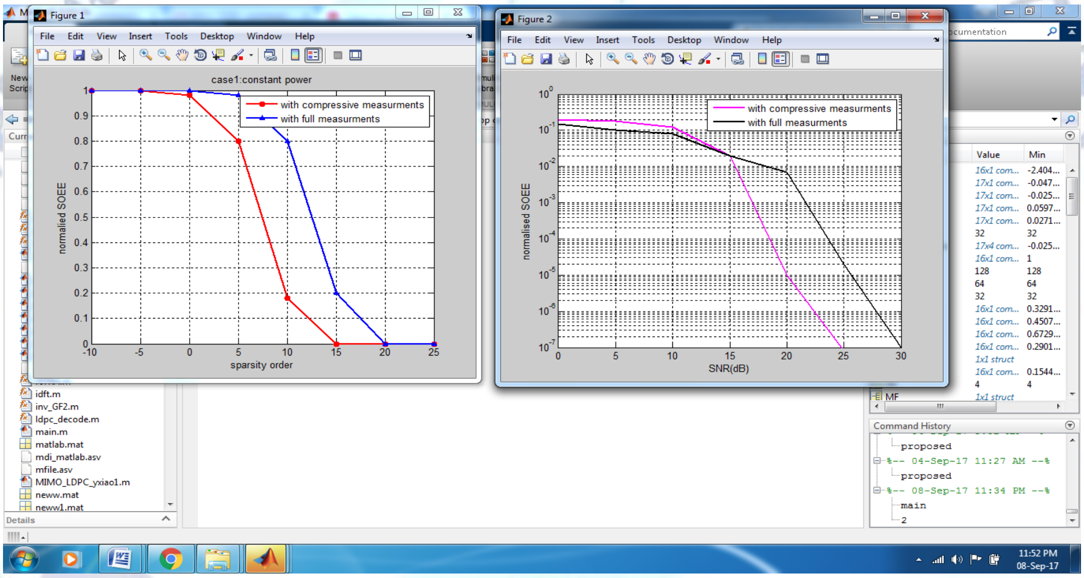
II. COMPRESSIVE SPARSITY ORDER ESTIMATION METHOD

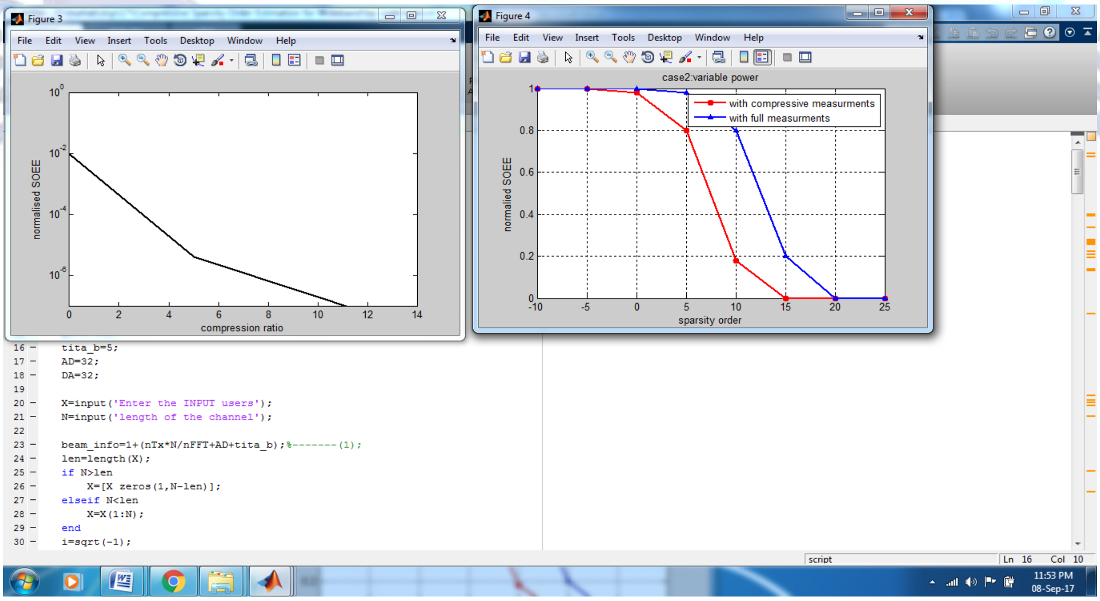
The SOE is the process of identifying the number of nonzero elements of a sparse vector and does not need to have the exact knowledge of their amplitudes or positions. The proposed compressive sparsity order estimation can be applicable in general settings. In this paper, this problem is mainly motivated by wideband CR scenarios where compressive SOE is the main issue for determining the suitable sampling rate at the receiver. To determine the suitable sampling rate at the CR receiver, most existing CS literature implicitly assumes that the sparsity order of the considered wideband spectrum is known beforehand. However, in practical CR applications, the actual sparsity order corresponds to the instantaneous spectrum occupancy of wireless users and it varies dynamically as the spectrum occupancy changes. Hence, the sparsity order is often unknown and only its upper bound can be measured based on the maximum spectrum utilization observed statistically over a time period. In practice, the determination of the sampling rate based on the upper bound can cause unnecessarily high sensing cost since the sampling rate depends on the sparsity order [2]. From the above discussion, it can be noted that it is crucial to adapt the sampling rate in accordance to the sparsity variation of the spectrum occupancy and thus tracking the instantaneous sparsity order is an important issue. In this context, we propose an eigenvalue-based blind SOE method which is based on the maximum eigenvalue of the measured signal's sample covariance matrix. Within the framework of compressed sensing, many theoretical guarantees for signal reconstruction require that the number of linear measurements n exceed the sparsity $\|x\|_0$ of the unknown signal $x \in \mathbb{R}^p$. However, if the sparsity $\|x\|_0$ is unknown, the choice of n remains problematic. This paper considers the problem of estimating the unknown degree of sparsity of x with only a small number of linear measurements. Although we show that estimation of $\|x\|_0$ is generally intractable in this framework, we consider an alternative measure of sparsity $s(x) := \frac{\|x\|_1^2}{\|x\|_2^2}$, which is a sharp lower bound on $\|x\|_0$, and is more amenable to estimation. When x is a non-negative vector, we propose a computationally efficient estimator $\hat{s}(x)$, and use non-asymptotic methods to bound the relative error of $\hat{s}(x)$ in terms of a finite number of measurements. Remarkably, the quality of estimation is dimension-free, which ensures that $\hat{s}(x)$ is well-suited to the high-dimensional regime where $n << p$. These results also extend naturally to the problem of using linear measurements to estimate the rank of a positive semi-definite matrix, or the sparsity of a non-negative matrix. Finally, we show that if no structural assumption (such as non-negativity) is made on the signal x, then the quantity $s(x)$ cannot generally be estimated when $n << p$.

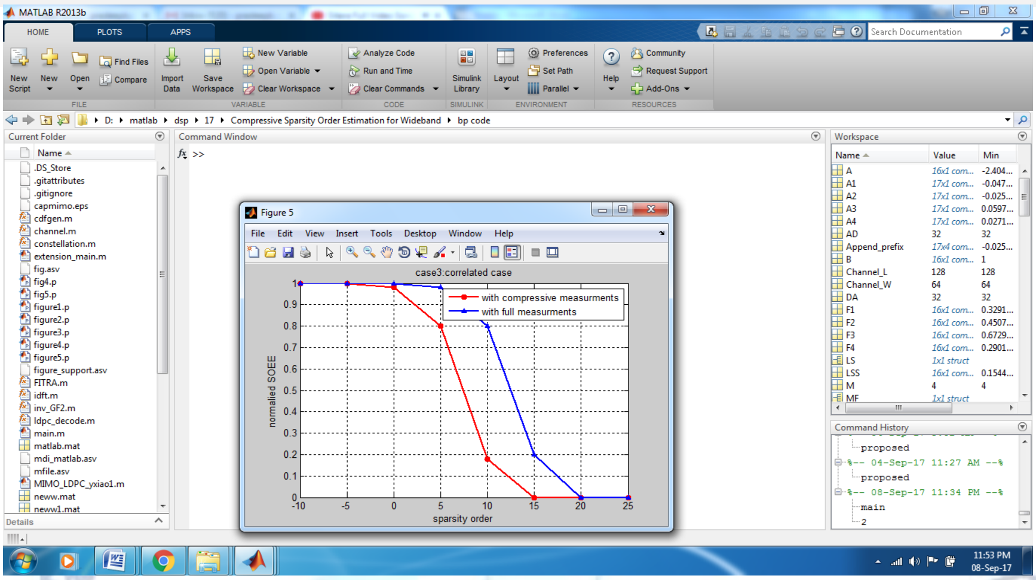
It's a nice combination of the observation that the quotient $s(x)$ is a sharp lower bound for $\|x\|_0$ and that it is possible to estimate the one-norm and the two norm of a vector x (with additional properties) from carefully chosen measurements. For a non-negative vector x you just measure with the constant-one vector which (in a noisy environment) gives you an estimate of $\|x\|_1$. Similarly, measuring with Gaussian random vector you can obtain an estimate of $\|x\|_2$.

Many emerging applications involve sparse signals, and their processing is a subject of active research. We desire a large class of sensing matrices which allow the user to discern important properties of the measured sparse signal. Of particular interest are matrices with the restricted isometry property (RIP). RIP matrices are known to enable efficient and stable reconstruction of sfficiently sparse signals, but the deterministic construction of such matrices has proven very dfficult. In this thesis, we discuss this matrix design problem in the context of a growing field of study known as frame theory.

III. RESULTS







IV. CONCLUSION

Finally, a novel technique has been proposed for estimating the sparsity order of spectrum occupancy within a wideband spectrum in the context of a wideband CR. First, the theoretical expressions for aepdf of the measured signal's covariancematrix have been derived for three different scenarios using RMT-based methods. More specifically, the following different scenarios have been considered: (i) constant received power scenario, (ii) varying received power scenario, and (iii) correlated scenario with the correlated multiple measurement vectors. Then the performance of the proposed method was evaluated in terms of the normalized SOEE for the considered scenarios.

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