



AIN SHAMS UNIVERSITY

FACULTY OF ENGINEERING

Electronics Engineering and Electrical Communications

## **Compressive Sensing for Cognitive Radio System**

A Thesis submitted in partial fulfillment of the requirements of the degree of

Doctor of Philosophy in Electrical Engineering

(Electronics Engineering and Electrical Communications )

by

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Master of Science in Electrical Engineering

(Electronics Engineering and Electrical Communications )

Faculty of Electronic Engineering, Menoufiya University, 2011

Supervised By

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Date: 24 October 2018

# Statement

This thesis is submitted as a partial fulfillment of Doctor of Philosophy in Electrical Engineering Engineering, Faculty of Engineering, Ain shams University.

The author carried out the work included in this thesis, and no part of it has been submitted for a degree or a qualification at any other scientific entity.

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# Thesis Summary

In the recent years, Cognitive Radio (CR) system is applied, as a magic solution, to provide an efficient use for any licensed spectrum. This efficiency is recognized by detecting the free sub-channels of the licensed spectrum, holes, and assigning them to the unlicensed users, Secondary Users (SUs). CR system can be performed either in a distributed or centralized network. In the latter form, the CR base station, Fusion Center (FC), is the only one that has the responsibility for this decision. This is done by the help of the collected samples from all SUs.

However, for a wide-band spectrum, a large number of the samples from each SU have to be transmitted to the FC. This causes an overload at the FC, especially for many SUs. To overcome this problem, Compressive Sensing (CS) paradigm has been introduced in the literature. It invests the sparse nature of the spectrum in the frequency domain at any time to reduce these samples into a small number of measurements.

CS paradigm can be separately employed at each SU to help it to get at least one measurement. The measurements from different SUs are collected and used by FC to detect the holes using one of the two CS recovery algorithms. These algorithms are the known as the first norm minimization and the greedy algorithms.

This thesis proposes a new recovery algorithm that comprises the features of the two CS recovery algorithms. The proposed algorithm depends on the utilization of the second norm minimization. To get the best performance of this algorithm, as in the greedy algorithms, a prior information about the number of licensed users (Primary Users (PUs)) has to be known. Unfortunately, this is impractical in real systems. To help the proposed recovery algorithm to defeat this challenge, it is suggested to be used with a proposed sensing scheme. The new scheme depends on grouping the SUs and segmenting the sub-channels of the licensed spectrum.

The new recovery algorithm with/without the recommended sensing scheme is first applied using one of the CS conventional measurement matrices (Gaussian matrix). However, when there is some cooperation between PUs and SUs, this matrix suffers from a variation of its size if any SU launches or terminates its transmission.

As a result, its entries values have to be changed and the new ones should be known at both SUs and the FC. To cope with this weakness, a new measurement matrix designed by Gallager Technique, Regular Parity Check (RPC), is recommended. One of the most important features of RPC matrix is its small processed time. This is due to its binary and sparse nature. However, its regularity nature restricts its performance.

To overcome the performance degradation, another proposed algorithm based on the use of the gradient-descent method is presented. This algorithm successfully improves the performance of RPC matrix by converting it into a semi-orthogonal one. In addition to keep on its regularity and sparsity nature, the proposed algorithm success to have a matrix with fixed entries values regardless of the number of active SUs at any time. Furthermore, the resulted matrix helps for the reduction of the complexity of the proposed recovery algorithm.

Simulation results are first conducted assuming the channels between SUs and the FC are Additive White Gaussian Noise (AWGN) and between SUs and PUs are noiseless. The results show that the CR system can detect the holes with high detection probability and low false alarm probability. However, when the channels between SUs and PUs are Rayleigh fading, the performance is degraded. To compensate the fading effect, a mechanism that depends on the time reversal is proposed. Simulation results show the effectiveness of this mechanism.

**Key words:** Cognitive Radio networks, Compressive Sensing, Gallager Technique,  $l_2$ -minimization, Matching Pursuit, Measurement Matrix, Orthogonal Matching Pursuit, Regular Parity Check Matrix, Semi-Orthogonal Matrix, Sparsity Estimation.

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