

Compressed Sensing for Wideband Signal

Processing

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Abstract

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Wideband Cognitive Spectrum Sensing

Cognitive Radio (CR) has been attracting many attention in recent researches with respect

to the potential better utilisation performance of limited spectrum resources. In this chapter,

we first propose an overview of cognitive radio networks. Then we focus on the bottleneck

in its front-end sampling devices and investigate the typical CS framework for spectrum

sensing in CR.

5.1 Introduction

As the wireless techniques keep fast developing, the limited spectrum resource seriously

restrictsthefastincreasingdemandformoreaccessiblebandwidth. Asaresult, thedynamic

spectrum access (DSA) becomes necessary and popular, which enables unused spectrum

accessed opportunistically, shown in figure 5.1.(a).

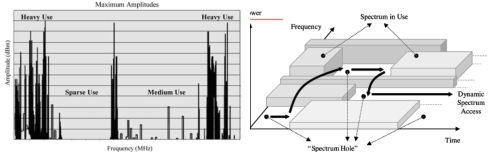
Following this idea, the cognitive radio (CR) develops aiming at optimizing utilisa-

tion of idle bands for communications, without doing harm to the primary users (licensed

spectrum) [1]. Correspondingly, the CR devices have to sense the environment (includ-

ing spectrum usage, noise level etc) quickly and accurately, and reconfigure themselves to

adapt the varying circumstance.



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(a) (b)

Figure 5.1: (a) The existence of unused spectrum resources; (b) The concept of spectrum

holes

Therefore, in cognitive radios, the first and important procedure is to sense the unused

bandwidth, termed as the spectrum holes and shown in figure 5.1.(b). If the band is detected

as unused, the CR networks will use it for further communication. Otherwise, the CR

moves to find other spectrum holes, or stays in the same band but avoid interference by

changing its transmission power or modulation model.

However, trends of communicating requires higher frequency and wider bandwidth. As

a result, signal acquisition significant is crucial according to the Nyquist sampling theory.

What’s worse, since CR should not generates additional interference to the licensed users,

CR must limits its working power to a relatively low level (if CR do not change its mod-

ulation model). The demand for sensing with low power contradicts with the requirement

for sensing in high sensitivity. Thus this contradiction makes the signal acquisition much

more difficult.

In conclusion, spectrum sensing becomes one of the most crucial problem for cognitive

radios, and it is still an open issue. Then, compressed sensing will be introduced to be

embedded into traditional spectrum sensing algorithms, in order to solve the problem and

enhance the overall performance.

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5.2 Spectrum Sensing

A cognitive radio supports the capability to select the best available channel [1], and the

main functions for cognitive radios in xG networks can be summarized as [2], where the

spectrum sensing to decide whether a particular sub-band of the spectrum is available or

not, without harmful interference with primary users. It is the first procedure in cognitive

radio networks where various parameters are detected for further spectrum management,

spectrum mobility and spectrum sharing.

5.2.1 Aim: Spectrum Usage Detection

According to the aim of spectrum sensing, the main task becomes to decide whether a

particular sub-band of the spectrum is available or not, namely, to detect spectrum usage

situation. A widely accepted idea is to detect the signal existence from licensed users’

(primary users, PUs) communication at cognitive radio’s receivers: if the PU’s signal (in

the particular sub-band) are not detected, cognitive radios can access the band for further

communication; otherwise, CR cannot use the band.

5.2.2 Hypothesis Detection Model

In this subsection, the problem of detecting the signal existence from PUs is modelled by

two hypotheses in equation 5.1:

H0 : y[n] = w[n]

H1 : y[n] = w[n] + x[n]

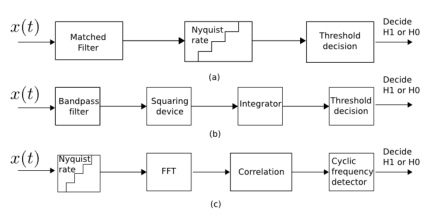
(5.1)

, where x[n] is the primary user’s signal, y[n] is the vectorial observation, w[n] is the

noise, and n refers to time slots. The hypothesis 1 suggests that the primary user’s signal

exists, while hypothesis 0 suggests no. Typically, the decision is made by comparing a

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Figure 5.2: Block diagrams for traditional narrowband detection architectures: a) matched

filtering detector; b) energy detector; c) feature detector

predetermined threshold with test statistic Λ(y) in equation 5.2:

Macintosh HD:Users:chenhao:Desktop:Screen Shot 2015-03-02 at 2.33.43 pm.png

Then the performance of a detector is quantified by the receiver operating characteristics

(ROC) curve, which presents the probability of detection PD = Prob(Λ(y) > α,H1) and

false alarm probability Pf a = Prob(Λ(y) > α,H0).

5.3 Traditional Detection Method

5.3.1 Narrowband Detection

In this section, typical spectrum sensing approaches are introduced. Narrowband sensing

algorithms can be suitably applied when the channel frequency response is flat. The fol-

lowing figure 5.2 demonstrates most typical architectures in narrowband spectrum sensing.

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5.3.1.1 Matched filter

In the figure 5.2.(a), the matched filtering (MF) detector [3] is presented. when the signal

to be detected is perfectly known (i.e. mean and variance), the optimal test statistic is

produced by matched filter by correlating the received signal to a template. However, the

signal cannot always be known in practise, so sometimes it’s not applicable. Besides, the

carrier synchronisation is also a remained difficult problem.

5.3.1.2 Energy detector

In the figure 5.2.(b), the energy detector (ED) [4] is presented. In the case where the signal

to be detected does not present structure template, the ED can produce the optimal test

statistic by directly analysis the power and variance of the received signal. The implemen-

tation of ED is simple, but it suffers from poor detection results in low SNR environment.

Besides, the ED cannot distinguish different primary signals at the same time.

5.3.1.3 Feature detector

In the figure 5.2.(c), cycle-stationary feature detection (FD) [5] is presented. If discrimi-

nation for primary signals and higher detection performance are required, the FD exploits

the cyclic non-stationary features from primary signals. The cyclic features can be found

in many typical modulated signals, for instance, in the orthogonal frequency-division mul-

tiplexing (OFDM) contains cyclic features in correlation structure due to the cyclic prefix

(CP) between transmitted data. However, the computational cost is relatively high and long

running time delay is always existing.

5.3.2 Nyquist Wideband Detection

In the scenarios where the bandwidth is sufficiently larger than coherence bandwidth of

channel, wideband sensing is more suitable than narrowband sensing. For instance, it can

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be used for sensing the ultra-high-frequency (UHF) TV band, ranging from 300 MHz to

3 GHz, while the narrowband sensing providing single binary decision over whole spec-

trum is always not suitable for identifying individual spectrum access opportunities. The

following figure 5.3 demonstrates the typical architectures for wideband spectrum sensing

and detection.

5.3.2.1 Multiband joint detector

In figure 5.3.(a), the multiband joint detector (MJD) [6] is presented. The MJD first uses

serial-to-parallel conversion (S/P) to divide samples into parallel data streams, then it pro-

cess the FFT to divide spectrum X(f) into groups of narrowband spectrum. Then each

binary hypothesis detection is performed and joint optimised at last. The high sampling

rate and lower speed of joint optimisation is the main bottleneck.

5.3.2.2 Wavelet detector

In figure 5.3.(b), the wavelet detector [7] is introduced. The wavelet analysis of power spec-

tral density (PSD) can provide significant border symbols of two neighbour sub-bands, the

aim of detection becomes a spectral edge detection problem. However, the high sampling

rate is also the bottleneck.

5.3.2.3 Sweep-tune detector

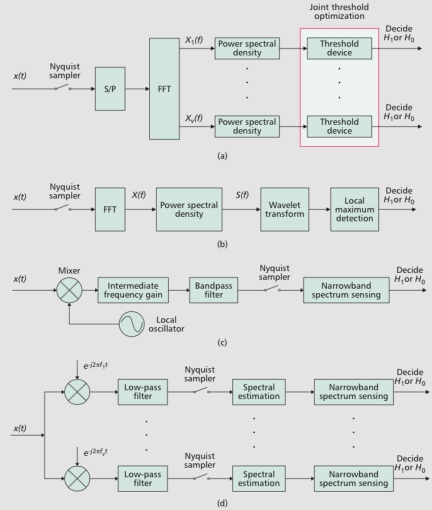
In figure 5.3.(c), the sweep-tune detector [6,8] is displayed. This detector uses a special

frequency mixing technique that ’sweep’ across the frequency range of interest, to down-

converts signals to a lower frequency. The adaptive local oscillator (LO) is used for ’sweep’

procedure. However, the procedure of ’sweep’ mixing generates too much time to wait.

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Figure 5.3: Block diagrams for Nyquist wideband detectors architectures: a) multiband

joint detector; b) wavelet detector; c) sweep-tune detector; d) filter-bank detector

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5.3.2.4 Filter-bank detector

Also using the idea of down-conversion, the figure 5.3.(d) shows the structure of filter-bank

detector [8]. Not only following the technique which ’sweep’ mixing the interest of signals,

it also applies parallel structure to speed up the processing time by using filter-bank. As a

result, the time cost of mixing reduces but the implementation cost largely increase.

5.4 Sub-Nyquist Wideband Detection

Different from Nyquist wideband detection, the sub-Nyquist spectrum sensing applies the

multi-coset (MC) sampling, multi-rate (MR) sampling, or compressed sensing (CS) to re-

duce the required sampling rate. Before talking about CS based sampling, first we take

brief look at MC and MR sampling.

5.4.0.5 Multi-Coset Sampling

The multi-coset (MC) sampling [9] applies blocks of parallel consecutive samples with

special time offsets to sample, so that each channel has a task of low-rate sampling. Then

joint spectrum recovery and further detection can be performed. The main difficulty is how

to perform sampling channel synchronisation with highly accurate time offsets. The quality

of the specific offsets is crucial for robustness in its spectral reconstruction.

5.4.0.6 Multi-Rate Sampling

The multi-rate (MR) sampling [10] uses various sampling rates to wrap different sparse

spectrum onto individual channels, and then use joint sparse spectrum recovery for further

energy detection. Time synchronisation is no longer needed compared to the MC. But

instead, the sacrifice is the hardware cost for parallel structure, as well as the increased

sampling rate compared to original CS although the MR’s sampling rate is still less than

Nyquist rate.

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5.5 CS based Detection Method

5.5.1 Introduction to Compressive Spectrum Sensing

Cognitive spectrum sensing is another typical application suitable for compressed sensing.

The applicability of Compressive spectrum sensing (CSS )mainly lies in two aspects:

**Sampling Rate**: The trend of higher frequency transmission is also suitable for cognitive

radio, which leads to higher rate sampling rate at receivers. Thus it’s reasonable to develop

the CS based spectrum sensing techniques to reduce the sampling rate.

**Flexibility and Energy**: The cognitive radio requires flexibility for sensing various types

of signals (TV signal, cell phone, satellites etc) in a relatively wide bandwidth. However,

normal wideband spectrum detection uses filtering or mixing for down-conversion (then

low-rate sampling). This approach require difficult analog implementations such as adap-

tive local oscillator(LO) for filter-banks(FB). Inversely, if the CS is used, then the system

can get wider sensing (frequency) ranges without the hardware of LO or FB.

Therefore, theCSbecomepopularincognitivespectrumsensing. Thefigure5.4demon-

strates the typical architectures in wideband spectrum sensing, and briefly analyse CS de-

tectors. The similar CS based architecture can also be viewed in chapter 2.

5.5.2 Compressive Detectors Overview

5.5.2.1 Demodulation based Detector

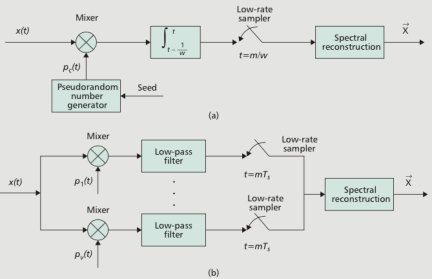
Figure 5.4.(a) presents the random demodulation (RD) based detector [11], which is an

analog-to-information converter (AIC) for finite-length and discrete-time signals, and con-

sists of pseudorandom wave generator, a mixer, and a low-rate ADC. The detailed archi-

tecture of RD is introduced in chapter 2. The reconstruction of RD sampled data involves

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Figure 5.4: Block diagrams for compressive wideband sensing architectures: a) random

demodulation based detector; b) modulated wideband converter-based detector

l1-norm minimization (e.g. based BP, LASSO) or greedy method (e.g. OMP). This design

is simple, but easily affected by model mismatches and design imperfections.

5.5.2.2 Modulated Wideband Converter based Detector

Figure 5.4.(b) displays the modulated wideband converter (MWC) based detector [12] for

the case where multichannel signals are designed to be detected. The MWC can be con-

sidered as a parallel structure of RD, and its architecture is introduced in chapter 2. The

reconstruction of MWC involves the multiple measurement vector (MMV) sparse recovery

which exploits the fact that the columns of original spectrum coefficients share the same

sparsity pattern. Compared to the RD, MWC provides robustness against the noise and

model mismatches.

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5.5.2.3 Cooperative Compressive Spectrum Sensing

Cooperativeversionsofspectrumsensingisanopenissue, whichaimsatsolvingthehidden

terminal problem [1] and improve sensing accuracy. The cooperative version of compres-

sive wideband sensing have been developed [13,14]. Here, individual radios can make a

local decision about the presence or absence of a primary user, and these results can then

be fused in a centralised or decentralised manner. However, a greater cooperation gain can

be achieved by fusing all the compressed measurements, again in a centralised or decen-

tralised manner. In general, such measurement fusion requires that each cognitive radio

knows the channel state information (CSI) from all primary users to itself [13], which is

cumbersome. But recent extensions show that measurement fusion can also be carried out

without CSI knowledge [15].

5.5.3 An Instance: CS based Cognitive Radar System

In [16] the CS is embedded to enhance the performance of cognitive radar that use wide

operating frequency bandwidths for spectrum sensing and sharing. The compressive cog-

nitive radar utilises the typical CS techniques, including the random demodulation (RD)

for signal acquiring, basis pursuit de-noising (BPDN) algorithm and discrete cosine basis

(DCT)forsparsereconstruction, andclassicalenergydetector(ED)forhypothesisanalysis.

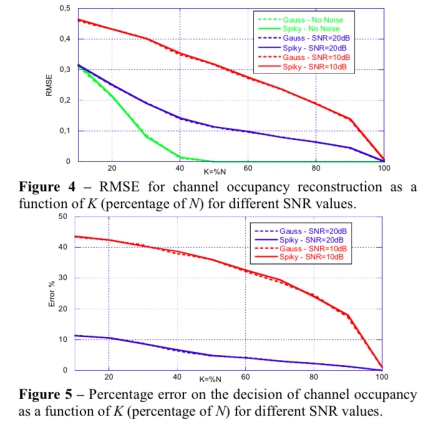
The experimental results figure 5.5 shows the CS based radar has appealing perfor-

mance in low sampling rate (using only < 30% of the total samples of the original signal)

and low detection error in high SNR cases. But in low SNR environment, the proposed

system still struggles and suffers.

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Figure 5.5: Block diagrams for mean square error and error detection performance of the

proposed compressive cognitive radar systems

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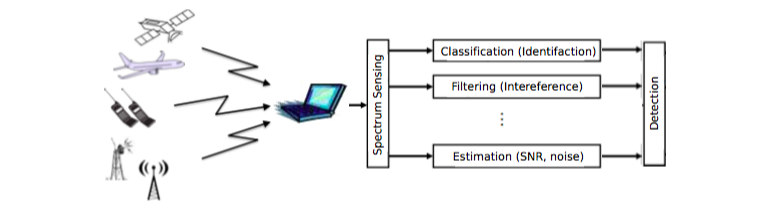


Figure 5.6: Block diagram of hybrid signal sensing, processing and detection in cognitive

spectrum sensing

5.6 Further Sensing Task: Hybrid Signal Processing

According to the aim of spectrum sensing that we have talked in section 5.2.1, the main

task is to detect the signal existence of licensed users’ (primary users, PUs) from cognitive

radio’s receivers.

Practically, in order to obtain high accurate detection result, a cognitive radio must keep

monitoring almost every useful ’clues’ to prove whether a spectrum band is used or not.

Such clues (in physical layer) contains various information such as signal to noise ratio

(SNR), modulation mode, primary signal bandwidth, and primary signal power etc.

As listed, there are too many informations to monitor at cognitive radios’ receivers,

so most of spectrum sensing algorithms only detect parts of the listed information, for

example, some monitor power (energy detection, ED), some check partial signal (matched

filtering detection, MFD), and others detect cyclic features (feature detection, FD).

As many those methods successfully accomplish the task in different scenarios, such as

ED works well in high SNR cases, FD performs well where primary signals contains strong

periodic information, however, one of the key aims of designing a modern network, is to

make the network flexible or heterogeneous enough, where hybrid types of primary signals

communications are mixed, and various parameters (SNR, noise, power modulation type)

based communications are time-varying, and different kinds of wireless devices (e.g. TV,

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mobile phone, radar) are allowed to access, shown as Figure 5.6. This demand gives rise to

a significant uncertainty in signals’ appearance, communication quality, and so on. In most

practical cases, hybrid signal communication will co-exist.

As a result, for a higher detection results in hybrid signal communication cases, some

pre-processsing methods (before final detection) such as filtering, estimation and classifi-

cation should be considered, these basic DSP techniques are regarded as useful auxiliary

methods for further complex detection. In other words, in cognitive radio, although detec-

tion is still a main task, but in order to efficiently detect co-existed primary signals under

time-varying parameters, the following methods are imperative for discriminating useful

information faster and more accurately. Those assistant methods include filtering (e.g. in-

terference cancelling), classification (e.g. hybrid signal identification), and estimation (e.g.

SNR, noise prediction).

As those assistant processing are traditional DSP methods, how to suitably implement

them to process CS sampled data is a big deal, because the CS sampled data are randomly

projected by groups of independent sensing vectors while traditional DSP algorithms are

aiming at data sampled by Dirac delta waveforms (spikes). The different sensing forms

lead to the incompatible of CS data and traditional DSP. Thus, if we want to add DSP pro-

cedure to improve the efficiency for the CS based hybrid CR signal spectrum sensing, the

CS reconstruction is often needed before sending CS data to traditional signal processing.

However, as later we will mention, the CS reconstruction is time-consuming and energy

costy, and thus become a performance bottleneck.

This problem presents us a further important issue for hybrid signal’s processing in CS

based cognitive radio, and more details will be introduced as our future research directions

in chapter 6.

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5.7 Challenges and Discussion

The compressed sensing based wideband spectrum sensing for cognitive radio provide its

outstanding feature in reducing the sampling rate. However, the corresponding drawbacks

emerge in real-time ability and energy consumption, mainly due to its computational ex-

pensive non-linear reconstruction and energy consuming characters.

5.7.1 Long-Time Feedback Delay

Accuarcy is cruical for primary detection. Hence, if we applies CS for sampling, the con-

vex optimisation (e.g.basis pursuit) is always needed for data recovery since it provides

better accuracy and robustness comparing to greedy methods (chapter 2). However, con-

vex optimisation is time consuming, which cause too long time to fast feed-back. Since

feed back is very important for CR, which is responsible to avoid interference and quick

reconfiguration, agility and reconfigurablity may reduce.

5.7.2 Mismatch for Traditional Signal Processing

The reconstruction algorithms for CS is non-linear, which indicates that the recovered data

are not directly suitable for conventional digital signal processing where traditional recov-

ering only requires cardinal sinc interpolation (linear process). This brings difficulty in

directly reuse the traditional method for sensed data.

5.7.3 High Energy Cost

TheheavyreconstructionforCSnotonlybringslargetime-delay, butalsoadditionalenergy

cost. Compared to linear recovery in traditional approaches, the CS based signal detection

additionally required the block for spectrum recovery before further hypothesis detection.

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5.8 Conclusion

Cognitive radio has been widely used and attracting many research attentions in its spec-

trum sensing techniques. In this chapter, traditional sensing approaches such as energy

detection and feature detection are introduced. In order to solve the detection task for

wideband and high frequency signals, compressed sensing based spectrum sensing (CS-

CSS) is introduced and demonstrated. However, the compressively sampled data does not

directly match the traditional processing algorithms.

Thenherecomesthequestion: whatifwedirectlyperformhypothesisdetectionwithout

CS reconstruction? If the idea is achievable, the additional energy cost will be eliminated

so that the entire energy reduces. Besides, not only detection, if we can expand this idea

to filtering, estimation, then more intelligent-based scheme for cognitive radio can be sup-

ported in physical layer. The answer refers to our future research aims that shown in the

next chapter.

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Chapter 6

Future Work: Novel Signal Processing

for CS Spectrum Sensing

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