Compressed Sensing based Jammer Detection Algorithm for Wide-band Cognitive Radio Networks

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***Abstract*—This paper proposes a new algorithm for jammer detection in wide-band (WB) cognitive radio networks. We consider a WB which comprises of multiple fixed length narrow-band sub-bands (SB). These SBs are occupied by narrow-band signals which can be legitimate users or a jammer. To reduce the overhead of the analog-to-digital conversion (ADC), compressed sensing (CS) is performed first. CS allows us to estimate a WB spectrum with sub-Nyquist rate sampling. After that, energy detection is applied to identify the occupied sub-bands (SB). Then, for each occupied SB, some waveform parameters such as signal bandwidth and power spectral density (PSD) levels are compared with licit user database to classify the observed signal as a licit user or a jammer. In the end, performance of the proposed algorithm is shown with the help of monte carlo simulations under different empirical setups.**

I. Introduction

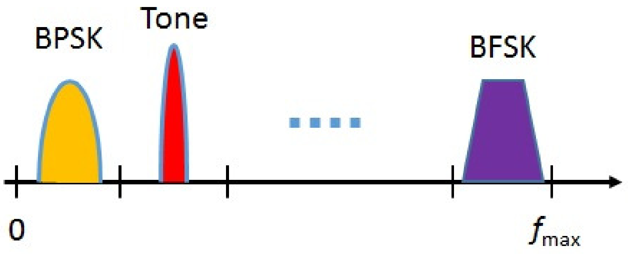
Federal Communications Commission (FCC) of the U.S. reported in [1] that some spectrum bands are largely under-utilized in particular geographic locations at particular times. This opened up new field of play for the wireless communication researchers to exploit these un-used licensed frequency bands for utilization by the unlicensed users. As a consequence, cognitive radios [2], [3] attained much popularity over the last decade. Cognitive radio is a technology that allows these unlicensed users to access the spectrum when licensed users are idle. Thus, cognitive radio has emerged as the enabling technology for Dynamic / Opportunistic spectrum access (DSA / OSA). In order for a cognitive radio to work, it must attain some information of its surrounding environment. This spectrum awareness comes from either radio frequency maps [4] or spectrum sensing.

There are several methods for spectrum sensing such as energy detection, cyclo-stationary detection or matched filtering [5]. Among these, despite its poor performance at low signal-to-noise ratios (SNR), energy detector is a popular choice due to its low implementation complexity. Of late, researchers have shown a good deal of interest in the study of energy detectors in both narrow-band [6]–[8] and wide-band (WB) regimes [9]–[11]. Specifically, the task of spectrum sensing becomes much more challenging for WB radios due to the requirement of high (at or above Nyquist) sampling rates. Because of this, high rate analog-to-digital converters (ADC) are required which increases the cost of the cognitive radio.

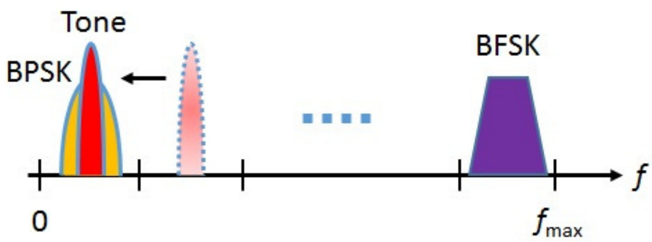
To alleviate the requirements of such high sampling rates, compressed sensing (CS) [12] has clutched some serious attention from the signal processing community over the past few years. According to the theory of CS, a sparse signal can be recovered from random samples taken at sub-Nyquist rate. Signal sparsity is the fundamental requirement for CS to work and in the context of cognitive radio networks, it is a practical assumption because not all frequency bands are occupied all the time in all geographical locations [1], [9]. Hence spectrum of the cognitive radio network is sparse in frequency domain due to low occupancy by the licensed users. Signal estimation using CS requires non-linear optimization to find the sparsest solution. This could be achieved by means of greedy algorithms such as Matching Pursuit (MP) [13] or Orthogonal MP [14]. The other solution is the use of Convex Programming as in Basis Pursuit (BP) algorithm [15].

Radio frequency (RF) jamming refers to the process of illicit RF transmission on one or more RF channels with the goal of disrupting the communication of the targeted system. Whereas RF jamming and anti-jamming are concepts almost as old as the wireless communication itself, recent advances in Cognitive Radio technology enable devising and deploying advanced, self-reconfigurable jamming [16] and anti-jamming solutions [17]. An anti-jamming system based on the Cognitive Radio technology may use the spectrum sensing information to detect potential jamming entities, and take proactive measures to ensure communication continuity and security. Furthermore, it may collect a history of the observations, and use it to devise anti-jamming tactics with even higher probability of success. For example, in case of a frequency hopping spread spectrum (FHSS) system, the Cognitive Radio may modify its hopping pattern to avoid the channels frequently occupied by the potential jamming entities [18]. In order to do so, a reliable jammer detection algorithm needs to be implemented.

This work introduces a CS based algorithm for jammer detection in WB spectrum. Spectrum is considered to be occupied by various narrow-band signals which can be classified either as legitimate signals or jammer signals. Each narrow-band signal can occupy a fixed length sub-band (SB) within the WB spectrum. The first step of the algorithm is the estimation of WB spectrum with CS technique to cope with high rate sampling. For the demonstration purpose, we choose to implement a conventional CS approach, i.e., BP. To find the sparsest solution, BP requires to solve the complex optimization problem for an under-determined system of equations. The Primal-Dual (PD) interior-point method



(a)



(b)

Fig. 1: (a) Wide-band spectrum divided into multiple sub-bands (SB) and each SB is occupied by a narrow-band signal. (b) Narrow-band jammer (Tone) jumps to the neighbouring SB to jam licit (BPSK) signal.

solves this convex optimization by using the classical Newton Method. After that, conventional energy detection is used to identify each SB either as idle or busy. Then, for each occupied SB, estimated waveform parameters such as its power spectral density (PSD) level and bandwidth, are compared with the parameters of the considered licit waveforms which are stored in a database. Based on this comparison, each of the detected signals is classified either as a licit waveform or a jammer. Finally, performance of the proposed algorithm is evaluated with the help of monte carlo simulations. To the best of our knowledge, this kind of jammer detection algorithm has not been introduced so far in the open literature.

The rest of the paper is organized as follows. Section II describes the system model and problem formulation. Section III outlines CS preliminaries and proposed algorithm. Experimental results are discussed in section IV. Finally, the paper is concluded in Section V along with some future directions.

II. System Model and Problem Formulation

Suppose that a Δ Hz of frequency spectrum in the frequency range $\{0, f_{max}\}$ is under observation for a WB communication network. This WB is divided into multiple, equal length SBs. Each of these SBs can be occupied by different narrow-band signals such as, tone (sine or cosine), binary phase shift keying (BPSK) signal, binary frequency shift keying (BFSK) signal, or any other narrow-band signal, as shown in Fig. 1(a). We consider that the narrow-band signals are confined within their respective SBs and there is no spill-over energy into the neighbouring SBs. Each of these received narrow-band signals experience multi-path Rayleigh fading due to the nature of the wireless channel. Furthermore, signals are effected by the additive white gaussian noise (AWGN) at the receiver.

For our system, we consider a single tone jamming signal. Tone jamming typically has high success rates against narrow-band signals, and may often be the best strategy for jammers with limited transmission power, as single tone jamming allows to concentrate all of the power on a single data channel. Let us assume that the targeted signal is BPSK-modulated and uncoded, and that the targeted receiver implements coherent detection. Then, the bit error probability $\mathrm{P_e}$ with single tone jamming present on the data channel of the targeted signal can be calculated as [19]:

$$\mathrm{P_e} = Q\left(\sqrt{2\frac{P_R}{\sigma_N}}\left(1 - \sqrt{\frac{2P_J}{P_R}sin(\theta^{P_J})}\right)\right) \tag{1}$$

where P_J is the received power of the jamming signal, θ^{P_J} is the phase of the jamming signal, P_R is the received power of the targeted signal, σ_N is the thermal noise power, and Q represents the Q-function. For simplicity of analysis, we assume that $P_J >> P_R$, resulting in $\mathrm{P_e} \approx 100\%$ whenever the jammer transmits on the same channel as the targeted transmitter-receiver pair. Furthermore, we disregard the effects of the jamming signal when it is placed on the channel complementary to the one used by the transmitter-receiver pair.

III. CS and Proposed Algorithm

In this section, we explain the preliminaries of CS as in [9], [11] and present our proposed algorithm. The observed time-domain WB signal can be expressed as,

$$r(t) = h(t) * s(t) + w(t) \tag{2}$$

where $h(t)$ is the channel coefficient between transmitter and receiver, $s(t)$ denotes the transmitted signal, $*$ denotes the convolution operation and $w(t)$ is the AWGN with zero mean and power spectral density σ_w^2.

For observing the frequency response of the received signal, an N-point discrete fourier transform (DFT) is taken on $r(t)$ to collect the frequency-domain samples into an $N \times 1$ vector r_f, as follows:

$$\mathbf{r}_f = \mathbf{D}_h \mathbf{s}_f + \mathbf{w}_f \tag{3}$$

where $\mathbf{D}_h = diag(\mathbf{h}_f)$ is an $N \times N$ diagonal channel matrix, and $\mathbf{h}_f$, $\mathbf{s}_f$ and $\mathbf{w}_f$ are the discrete frequency-domain samples of $h(t)$, $s(t)$ and $w(t)$, respectively. In general form, this signal model can be expressed as,

$$\mathbf{r}_f = \mathbf{H}_f \bar{\mathbf{s}}_f + \mathbf{w}_f \tag{4}$$

From the above expression, we can observe that the spectrum sensing task requires to estimate $\bar{\mathbf{s}}_f$ in (4) provided we have $\mathbf{H}_f$ and $r(t)$. Because we have a WB signal at our disposal, we can take advantage of the CS theory to relieve high sampling rate (Nyquist rate) ADC requirements. Various computationally feasible algorithms, such as, BP [15] or OMP [14], were developed to reliabaly estimate the received signal sampled at sub-Nyquist rate sampling.

We start by collecting the compressed time-domain samples at the receiver. For this, a compressed sensing matrix $\mathbf{S}_c$ is constructed to collect a $K \times 1$ sample vector $\mathbf{x}_t$ from $r(t)$ as follows:

$$\mathbf{x}_t = \mathbf{S}_c \mathbf{r}_t \tag{5}$$

where $\mathbf{r}_t$ is the $N \times 1$ vector of discrete-time representations of $r(t)$ at the Nyquist rate with $K \leq N$, and $\mathbf{S}_c$ is the $K \times N$ projection matrix. There are various designs introduced in literature for compressive sampler such as non-uniform sampler [20] and random sampler [21], [22].

Noting that $\mathbf{r}_t = \mathbf{F}_M^{-1} \mathbf{r}_f$, and given K compressed measurements, the frequency response $\bar{\mathbf{s}}_f$ can now be estimated in (4), as follows:

$$\mathbf{x}_t = \mathbf{S}_c^T \mathbf{F}_M^{-1} \mathbf{H}_f \bar{\mathbf{s}}_f + \tilde{\mathbf{w}}_f \tag{6}$$

where $\tilde{\mathbf{w}}_f = \mathbf{S}_c^T \mathbf{F}_M^{-1} \mathbf{w}_f$ is the noise sample vector which is white gaussian. In the context of CR networks, i.e., low spectrum occupancy by the licensed users, the signal vector $\mathbf{s}_f$ is sparse in frequency domain. The sparsity is measured by p-norm $||\bar{\mathbf{s}}_f||_p$, $p \in [0, 2)$, where $p = 0$ indicates exact sparsity.

Thus, equation (6) is a linear regression problem with signal $\bar{\mathbf{s}}_f$ being sparse. This signal $\bar{\mathbf{s}}_f$ can be reconstructed by solving the following linear convex optimization problem:

$$\hat{\mathbf{s}}_f = \arg\min_{\bar{\mathbf{s}}_f} ||\bar{\mathbf{s}}_f||_1, \quad s.t. \quad \mathbf{x}_t = \mathbf{S}_c^T \mathbf{F}_M^{-1} \mathbf{H}_f \bar{\mathbf{s}}_f \tag{7}$$

There are different methods to solve this optimization problem, for example, by means of Convex Programming as in BP [15] method or by usage of Greedy Algorithms such as MP [13] or OMP [14].

Having the estimated PSD $\hat{\mathbf{s}}_f$ of the wide-band spectrum, we need to find the presence or absence of a transmission signal in a certain SB. This decision can be simply taken by the use of energy detector using the estimated frequency response over that SB. Hence the test statistic will be

$$T_i = \sum_{m=(i-1)M+1}^{iM} \hat{\mathbf{s}}_f(m) \qquad i = 1, 2, ..., I \tag{8}$$

where i is the SB index, M is the PSD samples in each SB and m is the frequency carrier index. The PSD estimate can be expressed as

$$\hat{\mathbf{s}}_f(m) = \frac{1}{M} \sum_{m=1}^{M} |\mathbf{r}_f(m)|^2 \tag{9}$$

and the decision rule is given by

$$T_i \gtrless_{H_0}^{H_1} \lambda, \qquad i = 1, 2, ..., I \tag{10}$$

where H_0 and H_1 denote a transmit signal being absent or present, respectively and λ is the decision threshold.

After the energy detection decision process, the waveform analyses are performed for each occupied SB. Because of CS, we already have the bandwidths (due to fixed slicing of the WB) and estimated PSD in each SB. We assume that the algorithm has access to a database containing pre-defined parameters of the "legitimate" and / or "jammer" waveforms.

Algorithm 1 Pseudo-code for proposed algorithm

```
function JAMMER DETECTOR
    Initialize all SB states to "free"
    Set compression rate ← K/N
    Sample the WB using random sampling
    Construct the measurement matrix ← S_c
    Estimate the WB from compressed samples using BP
    Divide estimated WB into i SBs
    for i = 1 to I, do
        Compute test statistic (T_i)
        Compute threshold (λ) based on desired P_f
        Compare λ with T_i
        Decision ← H_0 or H_1
    end for
    if H_1 then
        Access the database
        Compare parameters (bandwidth, estimated PSD)
    with the database waveforms
        Decision ← Licit or Jammer
    end if
end function
```

Now, the parameters of the waveforms from occupied SBs are compared with the parameters from the database, eventually identifying each signal as either licit or jammer. The pseudo-code of the proposed algorithm is outlined in Algorithm 1.

The considered method is computationally inexpensive but poses some limitations, such as;
(1) High mis-detection rate due to simple energy detection or poor estimation at low compression ratios; and
(2) Relatively high rate of wrong identification compared to more advanced waveform analysis methods.
Alternatively, more complex detectors which achieve better performance such as cyclo-stationary detectors or matched filters could be used to minimize mis-detection rate. Furthermore, computationally more expensive waveform analysis techniques like cross-correlation in time domain or statistical signal characterization (SSC) methods [23] could be used. These techniques are not used in this work however they all impose themselves as viable future research topics.

IV. Experimental Results and Discussion

We consider a WB spectrum of 500 ΔHz under observation. This WB is divided into 5 SBs of equal bandwidth. Each of this SB can either be free or occupied by a narrow-band signal. For our experiments, we consider a BPSK signal to be a legitimate signal and cosine wave to be a jammer signal. The received signals are considered to be effected by multi-path Rayleigh fading and AWGN.

As explained in previous section, there are various method for estimation and reconstruction with CS such as BP, OMP or MP. For this study, we use the BP algorithm for estimation in the CS part. The proposed jammer detection algorithm is evaluated at varying compression ratios between 0.25 and 1.0. The detection threshold λ is computed by fixing the false

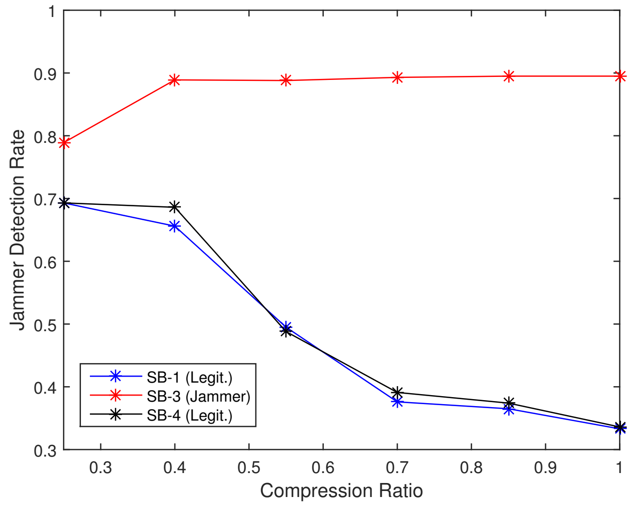


Fig. 2: Performance of Jammer Detection Algorithm at $P_f = 0.01, SNR = 5dB$ and various compression ratios. SB-1 and SB-4 are occupied by legitimate signal and SB-3 is occupied by jammer.

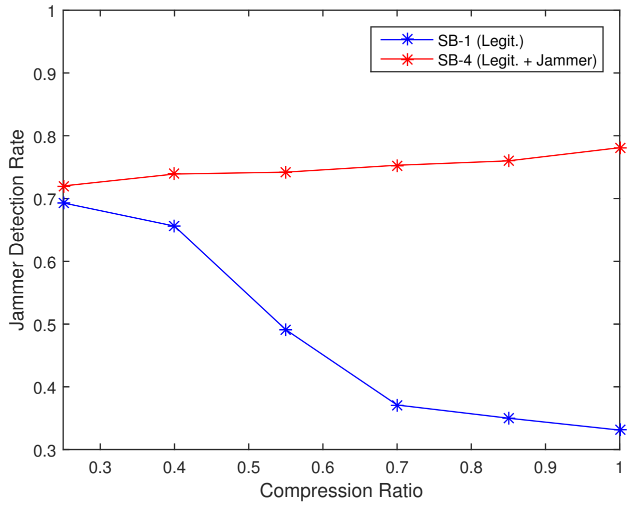


Fig. 3: Performance of Jammer Detection Algorithm at $P_f = 0.01, SNR = 5dB$ and various compression ratios. SB-1 is occupied by legitimate signal and SB-4 has both legitimate signal and jammer.

alarm rate $P_f = 0.01$. It is well known that energy detector performance degrades at low SNR values. Therefore, we set SNR level at a moderate level of 5dB to minimize mis-detection rate. Monte-carlo simulations were run for 1000 iterations.

We configure our system such that we placed the BPSK signals in SB-1 and SB-4 while jammer signal was placed in SB-3. In Fig. (2), is plotted compression ratio versus jammer detection rate for this configuration. It can be seen that jammer detection rate in SB-3 is around 0.9 at high compression ratios. It is because of good estimation and reconstruction, mis-detection rate (SB-3 identified as un-occupied) of the energy detector was low, specifically, 0.1 at $K/N = 1.0$. On the other hand, jammer detection rate drops to 0.8 at $K/N = 0.25$ while mis-detection was 0.15 and wrong identification of jammer as legitimate signal was 0.05. Likewise, jammer detection rate falls to 0.33 at $K/N = 1.0$ for SB-1 and SB-4 which is logical because both these SBs have legitimate signals. The correct identification of SB-1 and SB-4 was 0.56 while mis-detection rate was again 0.1 at 100% compression. The wrong identification of legitimate signal as jammer increases with decreasing compression ratios due to poor estimation and reconstruction. Hence at $K/N = 0.25$, mis-detection was 0.21 while correct identification falls to 0.09 while jammer detection rate increases to 0.7 as can been in Fig. (2).

Now we configure our system such that SB-1 is occupied by BPSK signal while jammer jumps into SB-4 thus jamming the SB-4 which is occupied by BPSK signal. For this configuration we plot the jammer detection rate versus compression ratio in Fig. (3). As can be observed, the jammer detection rate in SB-1 is same as before while that in SB-4 is dropped by approximately 0.1 magnitude. This is because there is BPSK signal present in SB-4 as well as Jamming signal and algorithm is identifying legitimate signal too. Specifically, at $K/N = 1.0$, jammer detection rate is 0.78 while legitimate detection rate is 0.17 and 0.05 is mis-detection. On the other hand, when $K/N = 0.25$, jammer detection rate drops to 0.72 while licit detection rate is same at 0.17 and 0.11 is the mis-detection rate. Increase in mis-detection at low K/N is once again due to poor estimation. We have a performance degradation when both legitimate and jammer signals are present in same SB. However, performance can be further improved by using a more complex detector, such as a feature detector or matched filter. Through these detectors, more parameters of the in-coming signals can be extracted such as carrier frequencies, modulation scheme or channel encoding. These parameters can then be used for rigorous comparisons with the licit signals parameters to differentiate between a legitimate user and a jammer. But these methods impose extra computation costs and time on the system to achieve better performance. Therefore, it is imperative to find a balance between the required performance and complexity of the system.

V. Conclusion and Future Work

In this paper, a CS based jammer detection algorithm was presented for WB cognitive radio networks. The WB was considered to be comprised of several narrow-band SBs of equal bandwidths. To relieve ADC complexity, CS was employed in the first phase for estimating and reconstructing the WB spectrum. After that, estimated parameters from CS were compared with the parameters of the licit waveforms' database to identify jamming waveforms in each SB. In the end, results were evaluated for various compression rates and different occupancy states of the WB spectrum with the help of monte carlo simulations.

The proposed algorithm appears to perform well within the limitations imposed by energy detection and by comparison of only estimated bandwidth and PSD. However, higher performance can be achieved by implementing more sophisticated detector such as cyclo-stationary detector or matched filter. Performance enhancement may also be possible by using more expensive and elegant waveform parameters comparison like SSC methods or cross-correlation in time domain analyses. All these methods impose themselves as capable and interesting future research topics.

Acknowledgements

This work was developed within nSHIELD project (http://www.newshield.eu) co-funded by the ARTEMIS JOINT UNDERTAKING (Sub-programme SP6) focused on the research of SPD (Security, Privacy, Dependability) in the context of Embedded Systems.

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