Experimental Study of Spectrum Estimation and Reconstruction based on Compressive Sampling for Cognitive Radios

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***Abstract*—This paper addresses the experimental study of the wide band signal estimation and reconstruction using the established compressive sampling (CS) methods. For this purpose, a hardware test bed was setup inter-connecting a wide band SDR based hand held military radio (SWAVE HH or HH), vector signal generator, bi-directional coupler, attenuators, PC and other auxiliaries. Real-world communication signals were created by the signal generator and SWAVE HH was used to scan these signals. The discrete samples from the HH were collected on PC for reconstruction and application of CS. It was shown that good reconstruction of the acquired wide band signal is possible with sub-Nyquist rate sampling by means of signal reconstruction under CS framework. In the end, mean squared error (MSE) performance is shown to indicate better estimation and reconstruction of the signal with higher compression rate and higher sparsity.**

I. Introduction

Software Defined Radio (SDR) is a communication device in which some or all of the physical layer functions are defined in software. Traditionally, Cognitive Radio (CR) is assembled upon SDR [1], [2]. CR is a technology that allows unlicensed users to access the licensed frequency bands opportunistically. Hence, spectrum awareness is of prime importance for CR terminals. Spectrum awareness, in addition to open database (as in IEEE 802.22), typically comes from spectrum sensing which can be achieved by means of different methods, for example, matched filter detection, cyclo-stationary detection or energy detection [3]. Matched filter is a coherent detector and requires a priori information of the licensed users' signals thus increasing the CR complexity. Cyclo-stationary detector make use of some of the inherent properties of the licensed users' signals and uses computationally complex algorithms to identify the spectrum holes. Energy detector is a non-coherent or blind detector which only measures the energy of the received signal, and takes decision on spectrum availability after comparing the measured energy with a predefined threshold. Each of these methods has its own pros and cons, however, energy detection appears as a preferred choice for CRs with limited computational power, due to their low implementation complexity.

Lately, there has been much interest shown by researchers on the analysis of energy detectors both in narrowband [4], [5] and wideband regimes [6], [7]. Nevertheless, the task of spectrum sensing becomes increasingly difficult for wideband signals. It is because the receiver requires to sample the wideband signals at or above Nyquist rates. This, in turn, requires very high-rate analog-to-digital converters (ADC) which increases the cost of the CR terminals. To overcome this shortcoming, compressive sampling (CS) [8] has stormed into the signal processing research for the purpose of spectrum estimation and reconstruction. Literature on CS shows that a sparse signal can be recovered from random or random like samples taken at sub-Nyquist rates. Due to low spectrum occupancy by licensed users, the signals in CR networks are typically sparse in the frequency domain. Recovery using CS requires intense, non-linear optimization to find the sparsest solution. One solution to this is by means of Convex Programming as in Basis Pursuit (BP) method [9]. BP is a technique for decomposing a signal into an optimal superposition of dictionary elements and the optimization criterion is the l_1-norm of coefficients. The other solution is the usage of Greedy Algorithms, such as Matching Pursuit (MP) and Orthogonal MP (OMP) [10], [11]. For instance, MP iteratively incorporates into the reconstructed signal the component from the measurement set that explains the largest portion of the residual from the previous iteration. OMP additionally orthogonalizes the residual against all measurement vectors selected in previous iterations.

This work addresses the applicability of CS approach to spectrum estimation and reconstruction to real world communication data acquired from a wide band SDR based hand held military radio (SWAVE HH or HH) [12]. For these purposes, a test bed was assembled for a frequency range of interest, consisting of a HH interconnected with the PC; vector signal generator; and the corresponding auxiliaries. 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 underdetermined system of equations. The Primal-Dual (PD) interior-point method solves this convex optimization by using the classical Newton Method. Performance of the scheme was evaluated for different values of compression rates. It was shown that through application of CS, sub-Nyquist rate sampling can achieve good signal reconstruction. This is particularly useful because it can reduce the cost incurred by high rate ADCs. In the end, performance is also shown in terms of Mean squared error (MSE) of the reconstructed waveform under different compression ratios.

The rest of the paper is organized as follows. Section II describes the system model and CS preliminaries. Section III outlines the test bed architecture while experimental results are presented in Section IV. Finally, the paper is concluded in Section V along with some future directions.

II. System Model and CS Preliminaries

Herein, we explain our system model along with the preliminaries of compressive sampling along the lines of [6]. The received time-domain wideband signal at the HH can be expressed as,

$$r(t) = h(t) * s(t) + w(t) \tag{1}$$

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

In order to observe the frequency response of the received signal, an N-point discrete fourier transform (DFT) is taken on $r(t)$. Collecting the frequency-domain samples into an $N \times 1$ vector r_f, we have

$$\mathbf{r}_f = \mathbf{D}_h \mathbf{s}_f + \mathbf{w}_f \tag{2}$$

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 written as,

$$\mathbf{r}_f = \mathbf{H}_f \overline{\mathbf{s}}_f + \mathbf{w}_f \tag{3}$$

Given the above expression, the spectrum sensing task boils down to estimating $\overline{\mathbf{s}}_f$ in (3) provided we have $\mathbf{H}_f$ and $r(t)$. However, since we have a wideband signal at our disposal, it will be beneficial to apply CS framework to relieve high sampling rate (Nyquist rate) ADC requirements. Recent advances in CS have demonstrated reliable signal reconstruction at sub-Nyquist rate sampling via computationally feasible algorithms, such as BP, MP or OMP.

At first, the compressed time-domain samples are collected at the receiver. For this, a compressive sampling matrix $\mathbf{S}_c$ is adopted to collect a $K \times 1$ sample vector $\mathbf{x}_t$ from $r(t)$ as follows:

$$\mathbf{x}_t = \mathbf{S}_c \mathbf{r}_t \tag{4}$$

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 [13] and random sampler [14], [15].

With the K compressed measurements, the frequency response $\overline{\mathbf{s}}_f$ can now be estimated in (3). Noting that $\mathbf{r}_t = \mathbf{F}_M^{-1} \mathbf{r}_f$, we can write

$$\mathbf{x}_t = \mathbf{S}_c^T \mathbf{F}_M^{-1} \mathbf{H}_f \overline{\mathbf{s}}_f + \tilde{\mathbf{w}}_f \tag{5}$$

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 CR networks, the spectrum occupancy by the licensed users is typically low. Thus the signal vector $\mathbf{s}_f$ is sparse in frequency domain with few non-zero entries. The sparsity is measured by p-norm $||\overline{\mathbf{s}}_f||_p$, $p \in [0, 2)$, where $p = 0$ indicates exact sparsity.

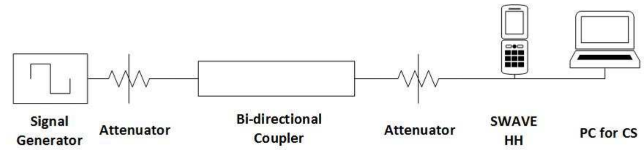

Fig. 1. Simplified block diagram of the assembled test-bed.

Thus, equation (5) is a linear regression problem with signal $\overline{\mathbf{s}}_f$ being sparse. This signal $\overline{\mathbf{s}}_f$ can be reconstructed by solving the following linear convex optimization problem:

$$\min_{\overline{\mathbf{s}}_f} ||\overline{\mathbf{s}}_f||_1, \quad s.t. \quad \mathbf{x}_t = \mathbf{S}_c^T \mathbf{F}_M^{-1} \mathbf{H}_f \overline{\mathbf{s}}_f \tag{6}$$

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

III. SDR Test-bed Setup

In this section, we will briefly outline the SDR test-bed setup which we used to obtain our required real world experimental data. More details about the test bed assembly can be found in [16].

A test bed was assembled for a frequency range of interest, consisting of a HH interconnected with the PC, vector signal generator and the corresponding auxiliaries. A simplified block diagram is shown in Fig. 1. Agilent E4438C signal generator is used to generate various real-world, as well as custom, wideband and narrowband signals. The signal generator is connected to Agilent 778D 100MHz - 2GHz dual directional coupler with 20 dB nominal coupling, by means of a coaxial RF cable. Use of coaxial cable allows us to repeat the experiment under same conditions, eliminating uncertainties of wireless transmission. On each end of the coupler, two programmable attenuators of 30 dB attenuation value were connected. HH was then connected to the attenuator by means of RF cable and was also connected to the PC through serial port. HH is a fully operational SDR transceiver capable of processing various wideband and narrowband waveforms. Currently, two functional waveforms are installed on the radio: SelfNET Soldier Broadband Waveform (SBW) and VHF/UHF Line Of Sight (VULOS), as well as the waveform providing support for the Internet Protocol (IP) communication in accordance with MIL-STD-188-220C specification [17]. HH has 12-bit analog-to-digital converter (ADC) which performs the sampling of incoming signals at very high rates of 250 Msamples/sec, and it is capable of scanning 120 MHz of wideband. The digitized signal is then issued to the FPGA, where it undergoes down conversion, matched filtering and demodulation. Being a military technology, several technical characteristics of SWAVE HH , i.e., processor specifications and more in-depth operational details are inclosable.

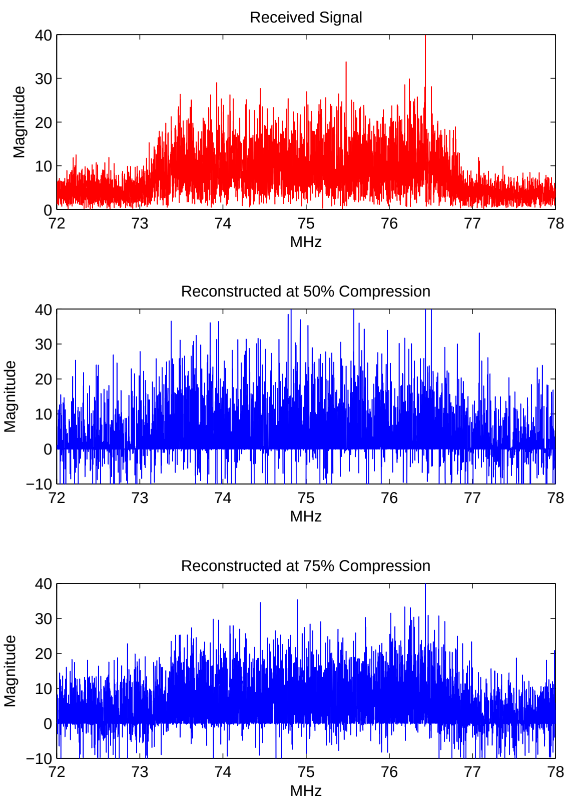

Fig. 2. (a) Received 3 MHz wide band gaussian waveform; (b) reconstruction at 50% compression ratio; (c) reconstruction at 75% compression ratio.

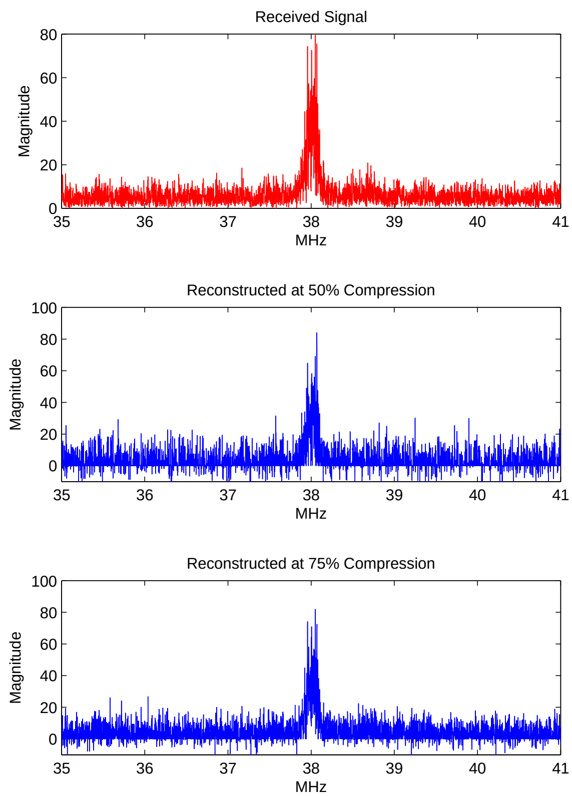

Fig. 3. (a) Received 250 KHz narrow band GSM waveform; (b) reconstruction at 50% compression ratio; (c) reconstruction at 75% compression ratio.

Several interfaces are available on the HH, namely, 10/100 Ethernet, USB 2.0, RS-485 serial, DC power interface and PTT. Ethernet connection on the SWAVE HH is used for the remote control of the HH, using Simple Network Management Protocol (SNMP) while serial connection is used for transferring the spectrum snapshots from HH to PC. Since the data transfer rate of the serial port is low, i.e., 115200 bits/s, therefore, real time transfer of samples is not possible from the ADC of HH. Because of this, 8192 samples are transmitted from the ADC over the RS-485 serial port every 1.3 seconds. It is a functionality hard-coded in the HH's FPGA. Specifically speaking, the output of ADC contains discrete samples of the wideband signal. These samples are stored in an internal buffer of the FPGA and output through HH's serial port to the PC, where they can be processed. Because 8192 samples make the waveform analysis a difficult task due to the low frequency resolution, multiple snapshots of the spectrum are taken and analyzed at once. Once that the satisfying number of samples is collected and transferred to the PC, CS may be performed.

IV. Experimental Results

For our experiments, we generated two different kinds of waveforms from the Agilent E4438C vector signal generator, namely;

1) 3 MHz wide band gaussian waveform, and
2) 250 KHz narrow band GSM waveform.

These two waveforms were centered at 75 MHz and 38 MHz carrier frequencies before transmission. At the receiver side, SWAVE HH scanned the entire 120 MHz of bandwidth to locate these waveforms. The HH outputs 8192 digitized samples every 3 seconds from its serial port. Because 8192 samples are not sufficient to observe a meaningful waveform, we capture multiple bursts, i.e., 8192×10 samples to construct meaningful waveforms. These samples are then gathered on a PC through the serial port for the application of CS.

Reconstruction: In Fig. 2, we show the received wide band 3 MHz gaussian signal in frequency-domain and its reconstructed versions with 50% and 75% of compression ratios. It can be seen that reconstruction at $K/N = 0.75$ appears better than the reconstruction at $K/N = 0.5$. The same trend is observable in Fig. 3 where we plot the 250 KHz GSM waveform with its reconstructed versions with compressed samples. However, the reconstruction of GSM signal appears better even with low K/N ratio of 0.5. It is because the GSM signal has more sparsity (or zero elements)

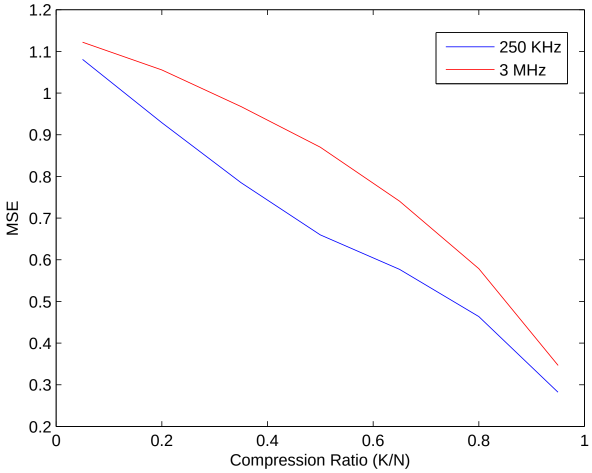

Fig. 4. MSE performance of 250 KHz GSM waveform compared with 3 MHz gaussian waveform at different compression rates.

compared to the 3 MHZ wide band signal, permitting for better reconstruction even with low compression ratios.

MSE Performance: We compare the normalized MSE of the reconstructed 3 MHZ signal with that of 250 KHz signal, at varying compression rates in Fig. 4. The normalized MSE is defined as

$$MSE = E\left\{\frac{||\hat{\mathbf{s}}-\mathbf{s}||_2^2}{||\mathbf{s}||_2^2}\right\} \tag{7}$$

where $\mathbf{s}$ is the signal vector sampled at Nyquist rate (or in our case at 8.192×10^4 samples) while $\hat{\mathbf{s}}$ is the estimated signal vector with compressed samples. We can see that MSE decreases with increasing K/N ratio. Furthermore, MSE performance of 250 KHz signal is better than the 3 MHz signal due to higher sparsity.

V. Conclusion and Future Work

In this work, we conducted an experimental study of the compressive sampling based wide band signal estimation and reconstruction. To gather real-world communication data, a hardware test bed was setup consisting of an SDR based radio, signal generator, PC and corresponding auxiliaries. Different real-world signals were captured by the HH and studied under CS framework. It was shown that reconstruction was successfully achieved with fewer than the Nyquist rate samples on real-world communication data. MSE performance was also shown to improve with higher sparsity in the data and higher compression ratios.

In future, we plan to connect two more SWAVE HH at the input port and scan various pre-installed waveforms from these HHs by means of a third HH. We also plan to study and implement various collaborative spectrum sensing algorithms based on the CS framework, which allows for more reliable spectrum holes detection in wide band regime and improves the overall spectrum utilization.

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