Improved Throughput Performance in Wideband Cognitive Radios Via Compressive Sensing

Sk. Shariful Alam, Lucio Marcenaro and Carlo S. Regazzoni
DITEN, University of Genoa
Via Opera pia 11a, I-16145 Genoa, Italy
e-mail: {shariful.alam, mlucio and carlo}@ginevra.dibe.unige.it

***Abstract*— Wideband spectrum sensing is a challenging task due to the constraints of digital signal processing (DSP) unit using in extant wireless systems. Compressive sensing (CS) is a new paradigm in signal processing, chosen for sparse wideband spectrum estimation with compressive measurements, thus provides relief of high-speed DSP requirements of cognitive radio (CR) receivers. In CS, whole wideband spectrum is estimated to find an opportunity for a CR usage requiring significant computation as well as sensing time, hence shrinkage the achievable throughput of CRs. In this paper, a novel model based CR receiver wideband sensing unit is addressed where a significant portion of the wideband spectrum is approximated through compressive sensing rather than recovering the total wideband spectrum. This model necessitates lesser sensing time and lower computational burden to detect a signal and as a result a level up of throughput is obtained. As a result, the sensing time gain improves the achievable throughput of the CRs which reflects on the simulation results and testifies the effectiveness of the proposed model. Therefore, a reduction of computational complexity is addressed without interfering with the detection performances, evaluated after spectrum estimation of a preferred band of interest by means of a well-known energy detector.**

Keywords*— *wideband spectrum sensing; compressive sampling; spectral estimation; l_1-norm minimization; analog-to-information converter.

I. INTRODUCTION

With the rapid growth of wireless systems and devices, the radio spectrum becomes scarce and recent research certifies that at any particular spatial region and time, spectrum is often heavily underutilized [1-2]. This vacant spectrum can opportunistically be utilized by the CR which permits the radio users to share their radio resources following improved spectrum efficiency. In the CR networks, the CR can dynamically regulate its transmission parameters. To regulate its radio frequency (RF) transmission properties, the CRs are required to sense the radio spectrum periodically for being aware of the licensed users. The enhancement of the spectrum efficiency can opportunistically be achieved by manipulating dynamic spectrum management schemes [3]. Conventional wideband spectral estimation requires very high sampling rates operating at or above the Nyquist rate [4]. A primary challenge in wideband sensing stems from the high RF signal acquisition costs of present-day analog-to-digital converters (ADCs) [5] and the ability for processing devices to handle a huge number of samples causing excessive memory occupancy as well as energy consumption.

CS is a method of acquisition of sparse signals allowing for very few samples that are much lower than the Nyquist sampling rate; the problem of signal recovery can be solved by convex optimization problem [6-9], called l_1 -norm regularization, that uses the basis pursuit (BP) [10] or some other greedy pursuits such as orthogonal matching pursuit (OMP) [11] or compressive sensing orthogonal matching pursuit [12]. These schemes provides an effective way to sense the discrete-time sparse (e.g., sparsity in frequency domain) signals and perfectly (or near perfectly) reconstructed with a few number of random projections. CS approach relies on the empirical observation as many types of signals or images can be well-approximated by sparse representation in terms of a suitable basis, i.e., considering only a few significant coefficients or number of non-zero (NNZ) elements in the signal vector. In order to deal with wideband signal acquisition purpose for compressible signals that enables sub-Nyquist data acquisition via an analog-to-information converter (AIC) or a random demodulator (RD) [13-14]. An AIC directly relates to the idea of sampling at the information rate of the signal. The CR with a wider spectral awareness could potentially exploit more spectral opportunities and obtain greater achievable rates. Therefore, wide band spectrum sensing techniques have attracted much attention among the researchers, working in CR regime [15]. In open literatures [15-16], authors are devoted to estimate the whole wideband spectrum to find a spectrum white space for opportunistic access of CRs. To estimate the whole wideband in CS domain implies computational burden as well as it requires more memory space to store data and hence prohibitive energy cost.

In order to design a robust spectrum sensing in wideband regime, this paper presents a model of CR receiver sensing module which estimate a significant part (which is highly sparse among the segments of the spectrum) of the entire wideband spectrum thus making computational complexity lower [17]. As soon as the wideband signal undergoes to different BPFs that pick out the preset value of RF band and divide the whole wideband spectrum into several frequency bins (FBs). Capitalizing the presence of sparsity in wideband spectrum, this paper aims to ascertain the highly-sparse frequency bin (HSFB) through average energy classification of each FBs. The energy estimation of a single FB is performed by taking random sub-Nyquist rate samples coming out from the AIC. After that, we develop spectral estimation of the HSFB via a convex optimization approach labeled as l_1-norm minimization. It is now checked the PU white spaces distribution inside the HSFB by using the energy detector (ED) [18] along with the throughput performance [18-19] of the proposed model. To conclude, comparison of the throughput of the proposed model to the single RF chain following the CS approach is illustrated.

The remainder of the paper is organized as follows. In section II, compressive sampling preliminaries are discussed and section III briefly describes compressive sampling via AIC. Signal model for the problem is presented in section IV. Section V describes the system modeling and problem statement while in section VI, performance analysis is carried out via simulations and some advantages of the proposed model are highlighted. Lastly, some conclusions are drawn in section VII.

II. COMPRESSIVE SAMPLING PRELIMENARIS

In the CS framework [3, 6-7] a real-valued, finite-length, one-dimensional time variant signal $x(t), 0 \leq t \leq T$, can be represented as a finite weighted sum of orthonormal basis functions (e.g., discrete cosine transform, discrete Fourier transform, etc.) as follows:

$$x(t) = \sum_{i=1}^{N} b_i \psi_i(t) = \psi b \tag{1}$$

where only a small number of basis coefficients b_i, representing the sparsity of wideband signal $x(t)$. Let the acquisition of an $N \times 1$ vector $\mathbf{x} = \boldsymbol{\psi}\mathbf{b}$ where $\boldsymbol{\psi}$ is the sparsity basis matrix of size $N \times N$ and $\mathbf{b}$ an $N \times 1$ vector with S number of non-zeros (e.g. significant elements compared to others) entries b_i. In case of sparse signals, an S-sparse representation of x can be seen as a linear combination of S orthonormal basis functions, with $S \ll N$ and it can be obtained by considering only S of the b_i coefficients in (1) that are significant non-zero elements, while zeroing the rest $(N - S)$ of the values representing less significant elements; this is the basis of the transform coding [7]. Sparsity is influenced by the fact that many natural and man-made signals are compressible in the sense that there exist a set of basis functions, $\boldsymbol{\psi}$ where the representation (1) has just a few significant coefficients [6-8]. It has been demonstrated that the original signal x can be recovered using $M = SO(log\, N)$ non-adaptive linear projection measurements on to a measurement matrix $\boldsymbol{\Phi}$ of size $M \times N$ which is incoherent with sparsifying basis, $\boldsymbol{\psi}$ [6-9]. The formation of sensing or measurement matrix $\boldsymbol{\Phi}$ is given by choosing elements that are drawn independently from a random distribution, e.g. Bernoulli, Gaussian, etc. Consequently, the measuring expression, $\mathbf{y}$ can be written as

$$\mathbf{y} = \boldsymbol{\Phi}\mathbf{x} = \boldsymbol{\Phi}\boldsymbol{\psi}\mathbf{b} = \boldsymbol{\Theta}\mathbf{b} \tag{2}$$

where $\boldsymbol{\Theta} = \boldsymbol{\Phi}\boldsymbol{\psi}$ is a matrix of size $M \times N$. As $M \ll N$, the dimension of $\boldsymbol{y}$ in (2) is much lower than that of $\boldsymbol{x}$, so there are theoretically infinite solutions to the equation. For these reasons, this problem is ill-posed and the reconstruction of the original signal is quite complex. Nevertheless, if it is satisfied that $\mathbf{x}$ is S-sparse with a proper basis of measurement matrix, $\boldsymbol{\Phi}$ (incoherent with $\boldsymbol{\psi}$) then the recovery of $\mathbf{x}$ can be attained with only $\boldsymbol{y}$ measurements by using the l_1-norm optimization method [6-7] as follows

$$\hat{\mathbf{b}} = arg\ \min_{\boldsymbol{b}} \|\mathbf{b}\|_{\mathbf{1}} \quad \text{s. t. } \boldsymbol{\Theta}\mathbf{b} = \mathbf{y} \tag{3}$$

This is a convex optimization problem that conveniently reduces to a linear program known as basis pursuit (BP) [10], iterative greedy algorithms [11], etc. CS method [6-7] confirms the recovery (accurately or near accurately) of the original signal is possibly acquired with sub-Nyquist rate samples which outfits with the ADC's available in the wireless systems.

III. COMPRESSIVE SAMPLING VIA AIC

To acquire sparse, band limited signals we introduce an AIC which is also entitled random demodulator. An AIC is theoretically similar to an ADC operating at Nyquist rate followed by the CS procedure. Fig. 1 displays the procurement of random samples through AIC. The benefit

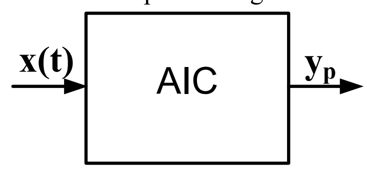

Fig.1: CS acquisition in proposed spectrum sensing method

of the AIC recognized as it avoids the need for a high-rate ADC. So, the system can be assembled with robust, low-power, readily available components even while it can acquire wider band signals than traditional ADCs [14]. The baseband (at CR node) signal $\mathbf{x(t)}$ is sampled using an AIC [13-14]. Let the output of the ADC which is the sampled signal of $\mathbf{x(t)}$, denoted by

$$\mathbf{x_p} = \left[\mathbf{x_{pN}}\ \mathbf{x_{pN+1}}\ \mathbf{x_{pN+2}}\ \ldots .\mathbf{x_{pN+N-1}}\right]^{\mathbf{T}}, p = 0,1, \ldots P \tag{4}$$

is a $\mathrm{N} \times 1$ vectors and the size of the measurement matrix $\boldsymbol{\Phi}_{\mathbf{A}}$ is $\mathrm{M} \times \mathrm{N}$, such that

$$\mathbf{y_p} = \boldsymbol{\Phi}_{\mathbf{A}}\mathbf{x_p} \tag{5}$$

So the output of the AIC denoted by the size of $\mathrm{M} \times 1$ vectors

$$\mathbf{y_p} = \left[\mathbf{y_{pM}}\ \mathbf{y_{pM+1}}\ \mathbf{yx_{pM+2}} \ldots \mathbf{y_{pM+M-1}}\right]^{\mathbf{T}}, p = 0,1, \ldots P \tag{6}$$

Those random samples are then considered for energy estimation. Then, estimation of the radio spectrum is performed by solving l_1-norm optimization problem as in (3).

IV. SIGNAL MODEL

The CRs in an opportunistic network need to decide the PUs occupancy status of a chosen frequency band within a single FB denoted by $n\ (n = 1,2, \ldots . N)$. To do so, the hypothesis test for detecting the occupancy status of PU in a band of interest is measured as $\mathcal{H}_{0,n}$ (absence of a PU) and $\mathcal{H}_{1,n}$ (presence of a PU). That is, we test the following binary hypotheses:

$$\hat{X}[n] = \begin{cases} W[n], & \mathcal{H}_{0,n} \\ H_n S[n] + W[n], & \mathcal{H}_{1,n} \end{cases} \tag{7}$$

where $\hat{X}$ is the spectrum of the band of interest estimated through the promising l_1-minimization scheme, discussed in [6-7]. H_n stands for the discrete frequency response between the PU and the CR, $S[n]$ is the primary signal transmitted within a frequency bin and $W[n]$ is complex additive white Gaussian noise (AWGN) with zero mean and unity variance.

An energy detector performance does not depend on the a-priori information of PU signal and less complex to implement [16] which make it popular in practical cases, therefore the signal energy is calculated over an interval of J samples by

$$E[n] = \frac{1}{N}\sum_{n=0}^{N-1}\left|\hat{X}_j[n]\right|^2 \tag{8}$$

where $\hat{X}_j[n]$ indicates the spectral estimation of the j-th sub-channel under concerning to CR and the decision parameter of the ED is given by

$$E[n] \underset{\mathcal{H}_{0,n}}{\overset{\mathcal{H}_{1,n}}{\gtrless}} \lambda_n \,,\ n = 1,2,\ldots.N \tag{9}$$

where λ_n is the decision threshold of a PU sub-channel of interest inside a frequency bin. Following [16], the signal energy can be described as

$$E[n] \backsim \begin{cases} \chi_{2j}^2, & \mathcal{H}_{0,n} \\ \chi_{2j}^2(2\gamma[n]), & \mathcal{H}_{1,n} \end{cases} \tag{10}$$

where $\gamma[n]$ denotes the signal-to-noise ratio (SNR) at the CR of a frequency band, and χ_{2j}^2 and $\chi_{2j}^2(2\gamma[n])$ denote central and non-central chi-square distributions, respectively. Both those distributions have degrees of freedom of $2j$. For simplicity, it is assumed that primary radios deploy uniform power transmission strategy and the medium access control (MAC) layer assures that the CRs keep quiet during each detection period while the PUs do transmit signals. The probability of detection, P_d and the probability of false alarm, P_{fa} can be calculated as proposed in [17]

$$P_{fa,n} = \Pr(E[n] > (\lambda_n|\mathcal{H}_{0,n}) \\ = Q\left(\left(\frac{\lambda_n}{\sigma_u^2} - 1\right)\sqrt{N/2}\right) \tag{11}$$

$$P_{d,n} = \Pr(E[n] > (\lambda_n|\mathcal{H}_{1,n}) \\ = Q\left(\left(\frac{\lambda_n}{\sigma_u^2} - \gamma[n] - 1\right)\sqrt{\frac{N}{2(2\gamma+1)}}\right) \tag{12}$$

where, λ_n denotes the threshold of a PU band of interest, σ_u^2 denotes the noise variance, N is the number of samples inside a band and N is composed of sensing time τ multiplied with the sampling frequency f_s e.g., $N = \tau f_s$ where $Q(\cdot)$ is the complementary distribution function of the standard Gaussian, i.e.,

$$Q(x) = \frac{1}{2\pi}\int_x^\infty \exp(-\frac{t^2}{2})dt \tag{13}$$

V. SYSTEM MODELING AND PROBLEM STATEMENT

Suppose that a CR receiver has employed with a band-pass filter bank as depicted in Fig. 2. Let the wideband signal, $x_c(t)$ of bandwidth W Hz is mutually shared among the PUs to a primary communication system and some part of the bandwidth is available for opportunistic accessing to the CRs in a particular geographic location and time. The wideband filter prior to the BPF preserves the concerned spectrum of particular frequency bands, and is set to have the bandwidth W Hz. Assume that the bandwidth of non-overlapped PU is B Hz and also the same bandwidth can opportunistically serve the necessity of a CR node for communication. Therefore, the possibility of maximum number of available channels are to be defined as $L \triangleq \frac{W}{B}$ and f_i is the center frequency of the i-th channel. Also, consider that the CR node is comprising with an wide-band antenna in order to probe the whole wideband time-domain signal $x_c(t)$.

Let the CR receiver has accommodated K number of identical BPFs, the outputs of the BPFs are denoted by x_k and each one has a bandwidth of equal size $w_k = \frac{W}{K}$ Hz, where $k = 1,2 \ldots K$. The wideband signal is fed into the filter bank ($\{H_k(f)\}_{k=1}^K$ consisting of $K < N$ wideband filters whereas $H_k(f)$ represents the transfer function of the k-th filter) which sets boundary for the wideband signal in several frequency bins, $w_k > B$ of identical dimension. To make the problem simpler, we assume that at least one PU sub-channel present in a FB, x_k at any timing instant.

The output of the k-th BPF is then sent to the RD as described in the paper [14] in order to obtain M_K randomized samples and those samples are intended for calculating the average energy E_k of a single frequency bin and compare those average energies E_k $(k = 1,2..K)$ at the energy estimate and compare block which is the most significant part in the proposed CR receiver block. One point is to mention here that the reliability of the energy comparison depends on the number of samples taken into account; the more the number of samples to be considered, the better would be the reliability to estimate the average energy of each frequency bin. Therefore, higher compression ratio M/N (large number of samples from RD) is taken into account for estimating average energy of each FB is calculated by considering identical number of random samples i.e. the same compression ratio for all frequency bins.

While comparing the average energy E_k of a bunch of samples corresponding to bandwidth w_k, the comparator also restore the samples corresponding to that FB which contains minimum average energy $E_{k(min)}$. We want to search for the frequency bin x_k with minimum energy as minimum energy gives the higher probability of having minimum number of PUs' presence within this FB, x_k. In addition to this, minimum number of PUs present in the FB, x_k augmenting the signal sparsity level (a few NNZ elements) in the frequency domain. After comparing the energy content of each FB, decimation of samples (as fewer samples would require for spectral recovery than energy estimation) are to be done of a suitable frequency bin (that contains minimum average energy $E_{k(min)}$ which is then considered to estimate the spectral magnitude $|\hat{X}_K|$ and this is prepared by applying the well-known l_1-minimization algorithm [7-8]. The HSFB provides a number of significant hints; first, it guarantees of having maximum number of PU sub-channels unoccupied which substantially exploit maximum chance to access for a CR node. Second, the more the sparsity, the better would be the spectral estimation which contributes improving detection performance. Third, spectral estimation of a single HSFB rather than entire wideband would ask smaller computational complexity.

Now, we move forward to an ED approach to find an inactive PU sub-channel for opportunistic use of a CR, and so we pay attention in reconstructing only the magnitude of the spectrum $|\hat{X}_k|$ regarding the FB, x_k. Now, the CR node decides the PU spectral vacancy status by using the ED test statistics, the decision of spectrum sensing regarding the sub-channel of interest.

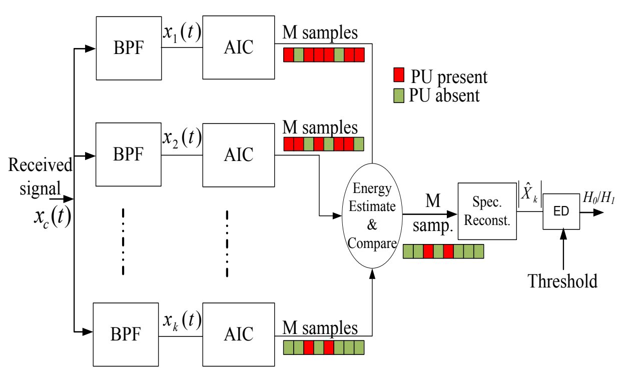

Fig.2. Schematic illustration of the filter based spectrum estimation via compressive sensing

A. *Achievable throughput of a single CR node*

To compute the achievable throughput for CR network we consider a simple problem which is collision free (as PU is absent and so no false alarm is caused by the CR) achievable throughput for CR network. Let us consider, τ is the time slot reserved for sensing operation and $(T-\tau)$ is the data transmission slot duration as shown in fig. 3 [18]. Also, denote C_0 as the achievable capacity of a CR network considering PU data transmission off and C_0 can be written as $C_0 = log_2(1+SNR_s)$, where $\mathrm{SNR_s}$ denote the signal-to-noise ratio of a CR link. Inside an interoperable network, we also consider PU data transmission, CR data transmission and reception are Gaussian, white in nature and independent to each other. For a particular band of interest, $P(\mathcal{H}_0)$ signifies the probability for which the PU data transmission is absent. Therefore, we recall the optimal achievable rate $\Re(\tau)$ from [17] is

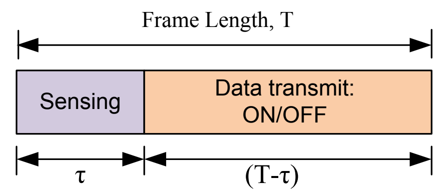

Fig. 3: Graphical structure of a typical frame of a CR data transmission

$$\Re(\tau) = C_0 P(\mathcal{H}_0)\left(1-\frac{\tau}{T}\right)\left(1-\mathcal{Q}\left(\alpha+\sqrt{N}\gamma\right)\right) \qquad (14)$$

where $\alpha = \sqrt{2\gamma+1}\mathcal{Q}^{-1}(P_d)$. From equation (14), it has been noticed that the achievable rate of a CR node varies with the sensing slot duration as well as frame duration e.g., the throughput is greater for shorter sensing time period τ with a fixed frame length T. Hence, we try to sort out a trade-off between the sensing length and frame length. As the miss detection probability, P_m can obligate with the possibility of data collision (a collapse of achievable throughput) with the PU transmission while the probability of false alarm P_{fa} recommends the CR to stop packet transmission during the frame interval though PU channel is idle at that instant which also decrease the throughput performance. We assume MAC layer of CR network guarantees that only one CR can have the accessibility of a PU sub-channel at a particular time to avoid the collisions among the CR nodes inside the network [18]. Therefore, collisions can only be possible between the CR and the PU.

VI. PERFORMANCE SIMULATIONS

We consider, at baseband, the wideband signal $x_c(t)$ contains a maximum of 32 non-overlapping sub-bands whose bandwidths $B=[1\sim2]\Delta$ Hz each and encode the sub-channels as $ch=\{ch_1, ch_2, \dots\dots ch_{32}\}$, with carrier frequencies, $f_c=[0\sim64]\Delta$ Hz, where Δ is the frequency resolution. In simulations, the numbers of BPFs are considered $K=4$ and the carrier frequencies f_c are chosen randomly such that the occupancy of PU bands $\{f_c\}_{c=1}^{17}$ satisfy in different FBs as $\{x_k\}_{k=1}^{4}=\{6,5,4,2\}$ with different sparsity levels (shown in fig. 2). The received signal, $x_c(t)$ at the input of the k-th BPF is as follows

$$x_c(t) = \sum_{n=1}^{N}\Lambda\cdot sinc\left(B_n(t-\partial)\right)\cdot cos\left(2\pi f_n(t-\partial)\right)+z(t) \qquad (15)$$

where $\Lambda=\sqrt{E_nB_n}$, $sinc(x)=\frac{sin(\pi x)}{\pi x}$, E_n signifies average energy level of PU sub-bands, ∂ denotes the a random timing offset between sampling branches and $z(t)$ is the AWGN as we assume the received wideband signal is corrupted by such type of noise of unit variance before come to the CR terminal. At the CR node, the received SNR of the active channels are considered 0 dB, 5 dB and 10 dB. To make simulation atmosphere relaxed, we consider frequency resolution Δ is 1MHz so the signal has a global bandwidth of $W=64$ MHz. In this setting, the number of Nyquist samples, $N=4096$ if the band was sampled at Nyquist rate for $T=32\mu s$. For energy estimation inside each FB we chose a compression ratio, M/N of 30% while the compression ratio, M/N has varied from 1% to 30% for spectral estimation.

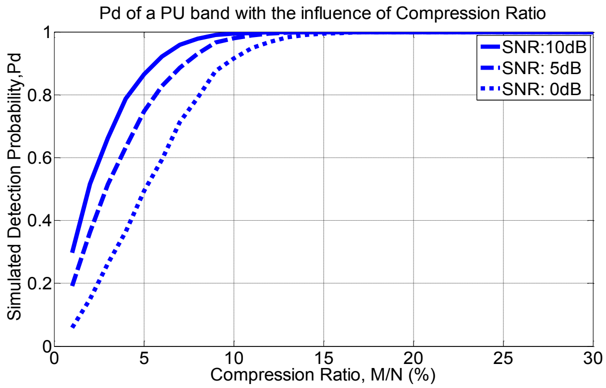

Fig. 4. Influence of compression ratio on the detection performance

The entries of the compressive measurement matrix $\mathbf{\Phi_A}$ be the Gaussian distributed with zero mean and variance $1/M$ and this random matrices permit the spectral estimation by using l_1-minimization. In order to form the measurement matrix $\mathbf{\Phi_A}$, discrete Fourier transform has been preferred as the sparsifying basis and then estimate the spectrum of the HSFB, x_k. Later, probability of detection has been checked out for a band of interest which may serve an opportunistic usage to a CR. In our case, one PU sub-channel frequency assists this purpose. If the numbers of PU sub-channels accommodate in a FB, $\mathrm{x_k}$ are equal to the number of EDs then it is possible to figure out the PU status simultaneously. However, a single ED can serve this job sequentially and hence has an impact on the opportunistic throughput at CR. The detection performance is drawn in fig. 3 that illustrates the influence of the compression ratio M/N on the wideband spectrum sensing performance which is comparable with a conventional one [15]. During simulation, we choose the statistical average of probability of detection, P_d of 10000 experimental results and set probability of false alarm $P_{fa} = 0.01$.

Later, to testify the effectiveness of the proposed approach with a CR system which estimates the entire spectrum, the throughput performance is investigated. To make easily understandable, we choose low regime SNR value of the PU system, e.g., SNR= -10dB, probability of detection $P_d = 0.90$ and probability of PU transmission is absent, $\mathrm{P}(\mathcal{H}_0) = 0.90$ when a CR node wishes to transmit. Intuitively, the sensing time, τ engaged for the proposed approach and the full spectrum estimation with a single RF chain followed by promising CS method is considered during simulation operation. Meanwhile, this sensing time, τ is applied in equation (14) to find the optimum throughput for a fixed frame length of 50ms and different SNR values as illustrated in fig. 5.

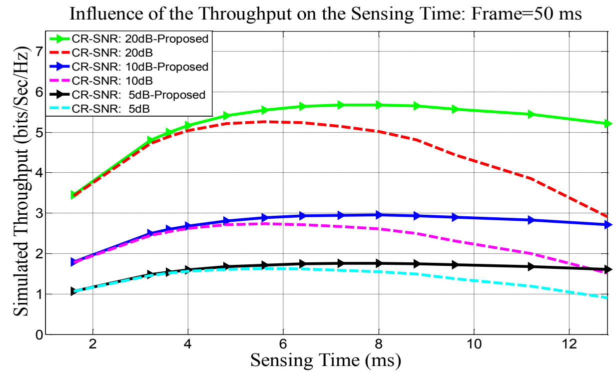

Fig. 5. Simulation of the achievable rate against sensing time for a fixed frame length

To proceed further, we again investigate (fig. 6) the optimum throughput of the same arrangement but this time a variation of the frame length is used with a fixed sensing time, $\tau = 4.7$ms. Fig. 6 also demonstrates that the proposed method outperforms with respect to a conventional CS based spectrum estimation approach.

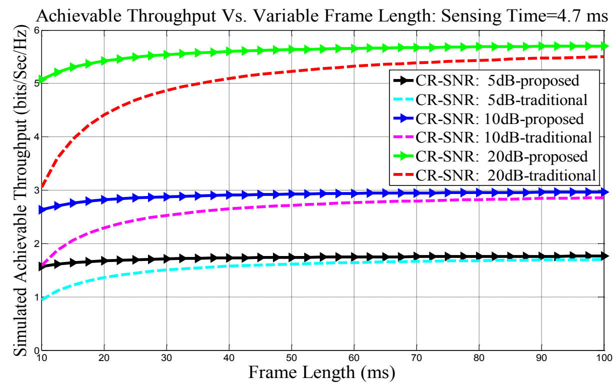

Fig. 6. Illustration of the achievable rate against Frame length for a fixed sensing period

There are several obtainable advantages of the proposed compressive sensing algorithm. Signal reconstruction via l_1-minimization involves $O(NlogN)$ operation (exactly, the computational burden is equal to the *number of iterations* $\times N \times log\, N$, where number of iterations is not usually easy to bound, but in worst-case, it can be bounded by N). With K number of filters, the computational burden is lessened in the order of $O(KlogK)$ and it requires only $O\left(\frac{N}{K} log \frac{N}{K}\right)$ operations. In the proposed approach, the desired spectrum is estimated considering only a few (M) number of random samples of the HSFB, x_k. Here, the number of samples are decreased by the influence of the number of filters K. Therefore, in the proposed scheme entails a reduced amount of arithmetic computations in the order of $O(KlogK)$. Therefore, less computation as well as improved throughput performance is obtained with the offered scheme in this paper. Proposed model outperforms existing wideband spectrum sensing methods, as it estimates only a single FB to find an opportunity for a CR thus obliges less sensing time as a result of significant improvement in achievable throughput as well as lower computational burden is validated.

An additional noteworthy statistics is to be distinguished here that the k-th filters having the bandwidth w_k greater than a single PU band, contributing a minor complexity of the filter design i.e. $1/w_k \times K/w_k = K/w_k^2$ over the conventional channel-by-channel scanning [16].

VII. CONCLUSION

This paper proposes an innovative block of CR receiver module for wideband spectrum sensing by the use of CS. Starting with a time domain signal, a single FB is estimated and detection performance has been explored through simulations to a band of interest for CR. Finally, achievable throughput performance of a static frame duration as well as static sensing length are compared to a traditional spectrum sensing methodology subsequent to a single RF chain with CS method. Corroborating simulation outcomes guarantee the worth of the proposed approach.

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