Low-Complexity Compressive Spectrum Sensing for Large-Scale Real-Time Processing

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***Abstract*—To overcome the challenges in high-speed sampling and processing of real-time spectrum measurement, compressive sensing (CS) theory has been implemented in wideband spectrum sensing. Moreover, to take full advantage of CS, the nonconvex l_ν-norm minimization algorithms are employed to reconstruct the wideband signals from compressive samples. However, solving these algorithms usually leads to relatively high computational complexity and sensing cost, especially when the dimension of wideband signals is high. Therefore, we propose a low-complexity compressive spectrum sensing algorithm that is suitable for large-scale real-time processing problem. The numerical and experimental results demonstrate that the proposed algorithm achieves the fast convergence speed and keeps the same accurate signal reconstruction with reduced computational complexity, from cubic time to linear time.**

***Index Terms*—Compressed sensing, cognitive radio, iterative algorithms.**

I. INTRODUCTION

IN RECENT years, the threat of spectrum scarcity has encouraged the development of dynamic spectrum access techniques over many licensed frequency bands which are underutilized either over time or geography domain, such as TV white space (TVWS) [1]. To enable these techniques without causing harmful interference to the incumbent systems, spectrum sensing which aims to provide fast and accurate detection of the spectrum is introduced. However, for the received signal over a wide spectrum, scanning the channels in a sequential manner will require a long sensing period and may cause interferences or missed opportunities. Therefore, directly acquiring the wideband signals is an ideal way to capture the instant spectrum changes. To alleviate the high rate of sampling and processing, compressive sensing (CS) was applied to implement the wideband spectrum sensing by exploiting the sparse nature of the underutilized wideband spectrum. CS theory indicates that the signal can be reconstructed from a few samples if it has the sparse structure [2].

To find the optimal solution that best matches compressive samples, the wideband signals can be reconstructed using certain optimization algorithms based on the l_0-norm minimization [2]. Since the l_0-norm minimization is an NP-hard problem, it is usually replaced by the l_1-norm minimization to find an equivalent solution. To further reduce the number of samples for signal reconstruction, the weighted l_ν-norm ($0 < \nu < 1$) minimization is proposed to replace the l_1-norm minimization in the reconstruction algorithm since the l_ν-norm minimization provides a closer approximation compared to the original l_0-norm minimization, which is nonconvex but could be effectively solved by iteratively reweighted least squares (IRLS) algorithms [3], [4]. However, those IRLS based CS algorithms lead to relatively high computational complexity and sensing cost, i.e., many iterations, to achieve the desired degree of accuracy.

In [5], to reduce the iterations in the l_ν-norm minimization, a database-assisted CS algorithm employs the channel historical power information from geo-location database for the weight calculation. However, the dynamic change of channel power information from geo-location database could severely degrade the reconstruction accuracy. In [6], without the prior channel information, an adaptively-regularized CS scheme is proposed to speed up the convergence of the signal reconstruction by reducing the required iterations of the l_ν-norm minimization. The AR-IRLS algorithm in [6] moves the estimated solutions along an exponential-linear path by regularizing weights with a series of non-increasing penalty terms and provides high fidelity guarantees to cope with the varying spectrum status.

The aforementioned research works aim to alleviate the sensing cost via the reduction in iterations of solving the l_ν-norm minimization, where the computational complexity of each iteration is still high. However, as the increasing of spectrum bandwidth and degree of spectrum resolution, solving the nonconvex l_ν-norm minimization would be difficult and costly since each iteration contains an inverse problem of the system matrix which takes $O(N^3)$, where N represents the dimension of target signals. In this letter, a low-complexity compressive spectrum sensing algorithm is proposed for large-scale real-time processing. It could keep the fast convergence speed of the previous algorithms such as [5] and [6] with reduced computational complexity by exploiting the diagonally dominant feature in the square of measurement matrix. Furthermore, the proposed algorithm is validated on both simulated signals and real-world signals. The numerical and experimental results indicate that the proposed algorithm can significantly reduce the computational complexity from cubic time to linear time in each iteration and maintain high reconstruction accuracy without the cost of more iterations.

Manuscript received January 15, 2018; revised February 20, 2018; accepted February 23, 2018. Date of publication February 27, 2018; date of current version August 21, 2018. The associate editor coordinating the review of this paper and approving it for publication was S. Ma. *(Corresponding author: Yuan Ma.)*

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Digital Object Identifier 10.1109/LWC.2018.2810231

II. Preliminary System Model

A typical non-cooperative compressive spectrum sensing scheme can be formulated as a three-step framework.

1) *Compressive signal acquisition:* Consider the received wideband signal $x(t)$ which consists of N_{sig} uncorrelated primary signals, such that $x(t) = \sum_{i=1}^{N_{\text{sig}}} s_i(t) + n(t)$, where $s_i(t)$ is the i-th primary signal and $n(t)$ refers to additive white Gaussian noise (AWGN) with zero mean and variance σ_n^2. Since the wideband spectrum is normally underutilized, the discrete Fourier transform (DFT) $\boldsymbol{x} = \{(x_1, x_2, \ldots, x_N)^T)| \boldsymbol{x} \in \mathbb{R}^N\}$ of $x(t)$ is a k-sparse vector, i.e., $|\{x_i : x_i \neq 0\}| \leq k$, which could be recovered from the compressive samples $\boldsymbol{y} \in \mathbb{R}^M$, where $M \in \mathbb{Z}$ (with $k < M < N$) refers to the dimension of $\boldsymbol{y}$. The compressive samples acquisition at a single node can be interpreted as a linear system: $\boldsymbol{y} = \boldsymbol{\Phi x} + \boldsymbol{\xi}$, where $||\boldsymbol{x}||_0 \leq k$, $\boldsymbol{\Phi} \in \mathbb{R}^{M\times N}$ represents the measurement matrix to collect samples $\boldsymbol{y}$ from the original signal $\boldsymbol{x}$, $\boldsymbol{\xi} \in \mathbb{R}^M$ is the noise perturbation, whose magnitude is constrained by an upper bound δ, i.e., $||\boldsymbol{\xi}||_2 < \delta$ and $||\cdot||_0$ represents the number of nonzero elements in the vector, which is also treated as the measure of sparsity.

2) *Signal reconstruction:* Under certain assumptions including the restricted isometry property (RIP) on $\boldsymbol{\Phi}$ and the signal sparsity bound [2], robust signal reconstruction with respect to the above linear system can be formulated as the following unconstrained minimization problem:

$$\boldsymbol{x}^* := \arg\min_{\boldsymbol{x}\in\mathbb{R}^N} \frac{1}{2}||\boldsymbol{\Phi x} - \boldsymbol{y}||_2^2 + \lambda||\boldsymbol{x}||_0, \tag{1}$$

where $\boldsymbol{x}^*$ is the reconstructed signal and constant parameter $\lambda > 0$ is introduced to balance the objective of minimizing the reconstruction error $||\boldsymbol{x} - \boldsymbol{x}^*||_2$ and the solution sparsity $||\boldsymbol{x}||_0$ according to the Lagrange multiplier theorem. However, problem (1) is NP-hard due to the l_0-norm minimization of $\boldsymbol{x}$. It was shown in [2] that the result of l_0-norm minimization can be equivalent to the solution obtained by the l_1-norm minimization which can be solved in polynomial time. Therefore, (1) can be approximated as

$$\boldsymbol{x}^* := \arg\min_{\boldsymbol{x}\in\mathbb{R}^N} \frac{1}{2}||\boldsymbol{\Phi x} - \boldsymbol{y}||_2^2 + \lambda||\boldsymbol{x}||_1. \tag{2}$$

However, (2) may not be the optimal solution to problem (1) since the l_1-norm optimization problem usually requires much more compressive samples [4]. Therefore, this poses challenges when the signal sparsity level is high. To that end, we propose to replace the l_1-norm in (2) with the l_ν-norm, where $0 < \nu < 1$, which is possible to achieve the exact reconstruction with the substantially fewer samples [4].

3) *Decision making:* To obtain the spectrum occupancy status, spectrum detection should be performed after signal reconstruction. The energy detection method [7] is adopted in this letter since it does not require any prior knowledge of the PUs, i.e., modulation type, with lower implementation and computational complexity compared with other conventional spectrum detection technologies.

III. Proposed Low-Complexity Compressive Spectrum Sensing Algorithm

Compared with the l_1-norm minimization in (2), the l_ν-norm minimization with $0 < \nu < 1$ leads to the better sparsity approximation performance with the fewer samples since it is an intermediate problem in the sense of norm minimization between (1) and (2) [4]. Therefore, we consider to replace the l_1-norm minimization with the l_ν-norm minimization for signal reconstruction in this letter. It can be given as

$$\boldsymbol{x}^* := \arg\min_{\boldsymbol{x}\in\mathbb{R}^N} \frac{1}{2}||\boldsymbol{\Phi x} - \boldsymbol{y}||_2^2 + \lambda||\boldsymbol{x}||_\nu^\nu, \quad 0 < \nu < 1, \tag{3}$$

where the penalty parameter $\lambda > 0$ is introduced to balance the reconstruction accuracy and the sparsity of minimization result as discussed in Section II. Since the choice of λ greatly influences the behavior of the spectrum reconstruction [6], in this letter, λ is optimized along with the signal reconstruction process as a function of the target signal, such that the problem in (3) can be transformed into the following form:

$$\boldsymbol{x}^* := \arg\min_{\boldsymbol{x}\in\mathbb{R}^N} \{F(\boldsymbol{x}) = \frac{1}{2}||\boldsymbol{\Phi x} - \boldsymbol{y}||_2^2 + \lambda(\boldsymbol{x})||\boldsymbol{x}||_\nu^\nu\}, \tag{4}$$

where $\lambda(\boldsymbol{x})$ projects the signal $\boldsymbol{x}$ as a positive real number. Without losing the numerical property of (3), we define the linear function of the form: $F(\boldsymbol{x}) = \varrho\lambda(\boldsymbol{x})$ [8] to preserve the convexity in each iteration and exhibits only a global minimizer regardless of the value of $\lambda(\boldsymbol{x})$, where ϱ is the coefficient representing the slope of the line and also controls convexity. It is straightforward to show that this linear form could keep the numerical property of the original problem unchanged. We substitute $F(\boldsymbol{x}) = \varrho\lambda(\boldsymbol{x})$ to (4) and therefore $\lambda(\boldsymbol{x})$ can be expressed as

$$\lambda(\boldsymbol{x}) = \frac{\frac{1}{2}||\boldsymbol{\Phi x} - \boldsymbol{y}||_2^2}{\varrho - ||\boldsymbol{x}||_\nu^\nu}, \quad 0 < \nu < 1. \tag{5}$$

However, it is general computationally hard and not guaranteed to obtain its global minimum due to the nonconvexity of the l_ν-norm minimization. It is shown in [4] that under certain assumptions such as the null space property (NSP) on measurement matrix $\boldsymbol{\Phi}$, the solution sequence generated by the IRLS algorithm converges to the local minimum as the sparsest solution that is also the actual global l_ν-norm minimizer. Each iteration of the IRLS algorithm corresponds to a convex weighted least squares subproblem that can be formulated as

$$\arg\min_{\boldsymbol{x}\in\mathbb{R}^N}\{\frac{1}{2}||\boldsymbol{\Phi x} - \boldsymbol{y}||_2^2 + \lambda(\boldsymbol{x})\sum_{i=1}^{N} w_i x_i^2\}, \tag{6}$$

where $w_i > 0$ for all $i = 1, 2, \ldots, N$ and could be defined as

$$w_i = \left(\left(x_i\right)^2 + \Omega_\epsilon\right)^{\frac{\nu}{2}-1}, \quad 0 < \nu < 1. \tag{7}$$

The parameter $\Omega_\epsilon > 0$ could be adopted to regularize the optimization problem in order to keep stability and ensure that any zero-valued component in the solution of certain iteration does not strictly prohibit the nonzero estimate at the next iteration [3]. To accelerate the convergence of the algorithm and prevent getting trapped into the wrong minimization results, a relatively large regularizer Ω_ϵ is proposed to initially regularize the weights. Then, the weights are quickly updated to allow the optimization process go deeper and achieve higher reconstruction accuracy by exponentially decreasing Ω_ϵ in the first few iterations. Moreover, the Ω_ϵ would descend slowly in the following iterations to avoid $\Omega_\epsilon \to 0$ but keeping Ω_ϵ sufficiently small to achieve high reconstruction accuracy.

To simplify the illustration, a generalizing function G_ν is defined as

$$G_\nu(\boldsymbol{x}, \boldsymbol{w}, \Omega_\epsilon) := \left[\frac{1}{2}||\boldsymbol{\Phi x} - \boldsymbol{y}||_2^2 + \lambda(\boldsymbol{x}) \sum_{i=1}^{N} w_i x_i^2\right], \tag{8}$$

where $\boldsymbol{x} \in \mathbb{R}^N$, weights $\boldsymbol{w} := (w_1, \ldots, w_N) \in \mathbb{R}_+^N$, and $\Omega_\epsilon \in \mathbb{R}_+$. From (8), we shall have

$$\lambda(\boldsymbol{x}) := \frac{G_\nu(\boldsymbol{x}, \boldsymbol{w}, \Omega_\epsilon) - \frac{1}{2}||\boldsymbol{\Phi x} - \boldsymbol{y}||_2^2}{\sum_{i=1}^{N} w_i x_i^2}. \tag{9}$$

We then substitute the linear form of adaptive penalty parameter $G_\nu(\boldsymbol{x}, \boldsymbol{w}, \Omega_\epsilon) = \varrho \cdot \lambda(\boldsymbol{x})$ into (9) as discussed before to obtain

$$\lambda(\boldsymbol{x}) = \frac{\frac{1}{2}||\boldsymbol{\Phi x} - \boldsymbol{y}||_2^2}{\varrho - \sum_{i=1}^{N} w_i x_i^2}. \tag{10}$$

To guarantee that the convexity of the function $G_\nu(\boldsymbol{x}, \boldsymbol{w}, \Omega_\epsilon)$ is unchanged in each iteration, the value of control parameter ϱ is determined by the proposed algorithm according to the samples vector $\boldsymbol{y}$ in practice.

Therefore, the result of iteration l can be defined as

$$\boldsymbol{x}^{(l)} := \arg\min \ G_\nu(\boldsymbol{x}^{(l-1)}, \boldsymbol{w}^{(l-1)}, \Omega_\epsilon^{(l-1)}). \tag{11}$$

Once $\boldsymbol{x}^{(l)}$ is obtained, we then update the parameters as

$$\Omega_\epsilon^{(l)} := \begin{cases} \left(1 + \frac{e^{-2l}}{h(\boldsymbol{x}^{(l)})_{k+1}}\right) h(\boldsymbol{x}^{(l)})_{k+1}, & \text{if } ||\Delta \boldsymbol{x}^{(l)}|| \le \frac{\epsilon^\nu}{100} \\ \Omega_\epsilon^{(l)}, & \text{otherwise,} \end{cases}$$

$$w_i^{(l)} := \left((x_i^{(l)})^2 + \Omega_\epsilon^{(l)}\right)^{\frac{\nu}{2}-1}, \qquad i = 1, \ldots, N, \tag{12}$$

where $h(\boldsymbol{x})_i$ is the i-th largest element of the set $\{|\boldsymbol{x}|_i, i = 1, \ldots, N\}$, k refers to the sparsity of the signal, and $\Delta \boldsymbol{x}^{(l)} = \boldsymbol{x}^{(l)} - \boldsymbol{x}^{(l-1)}$.

The problem (11) requires solving a weighted least squares problem that can be expressed in the matrix form:

$$\boldsymbol{x}^{(l)} = \left(\boldsymbol{\Phi}^t \boldsymbol{\Phi} + \lambda(\boldsymbol{x}^{(l-1)}) * \boldsymbol{W}^{(l-1)}\right)^{-1} \boldsymbol{\Phi}^t \boldsymbol{y}, \tag{13}$$

where $\boldsymbol{W}^{(l)}$ is the $N \times N$ diagonal matrix with $1/w_i^{(l)}$ as the i-th diagonal element and $\boldsymbol{\Phi}^t$ refers to the transpose of the sensing matrix $\boldsymbol{\Phi}$. Therefore, the efficiency of the proposed algorithm is mainly constrained by the inverse of the matrix $\boldsymbol{H} = \boldsymbol{\Phi}^t \boldsymbol{\Phi} + \lambda(\boldsymbol{x}^{(l-1)}) * \boldsymbol{W}^{(l-1)}$, which takes $O(N^3)$ time. It is difficult and costly to solve $\boldsymbol{H}^{-1}$ for many cases especially when the dimension of the original wideband signal is large. The conventional way to approximate the matrix inverse is conjugate gradient (CG) descent method. According to the observation that the matrix $\boldsymbol{H}$ is usually diagonal dominance due to the square of measurement matrix $\boldsymbol{\Phi}^t \boldsymbol{\Phi}$ is diagonal dominance, we proposed to utilize the preconditioned conjugate gradient (PCG) method which has better performance than CG [9]. To find the best approximation of $\boldsymbol{H}$, the preconditioner can be given by

$$\boldsymbol{P} := \arg\min_{\boldsymbol{Z} \in \boldsymbol{D}} \ ||\boldsymbol{H} - \boldsymbol{Z}||_2^2, \tag{14}$$

where $\boldsymbol{D}$ is a set of diagonal or ąřpseudo-diagonaląś matrices. Since $\lambda(\boldsymbol{x}^{(l-1)}) * \boldsymbol{W}^{(l-1)}$ is a diagonal matrix and $\boldsymbol{\Phi}^t \boldsymbol{\Phi}$ is diagonal dominance for the measurement matrix utilized in compressive spectrum sensing, e.g., random projection matrix for analog-to-information converter (AIC), partial Fourier matrix for multi-coset sampling and etc., $\boldsymbol{H}$ is diagonal dominance which could be approximated by a diagonal or pseudo-diagonal matrix $\boldsymbol{P}$. According to the diagonal dominance feature, the exact solution of (14) is given as

$$\boldsymbol{P} = (\overline{\boldsymbol{\Phi}^t \boldsymbol{\Phi}} * \boldsymbol{I} + \lambda(\boldsymbol{x}^{(l-1)}) * \boldsymbol{W}^{(l-1)}), \tag{15}$$

where $\overline{\boldsymbol{\Phi}^t \boldsymbol{\Phi}}$ denotes the average of all diagonal values of the matrix $\boldsymbol{\Phi}^t \boldsymbol{\Phi}$, which can be pre-calculated since $\boldsymbol{\Phi}$ is preset before the sensing. Therefore, compared with the inverse of the original matrix $\boldsymbol{H}$ which takes $O(N^3)$ time, $\boldsymbol{P}^{-1} = (\overline{\boldsymbol{\Phi}^t \boldsymbol{\Phi}} * \boldsymbol{I} + \lambda(\boldsymbol{x}^{(l-1)}) * \boldsymbol{W}^{(l-1)})^{-1}$ only require linear time $O(N)$. The proposed algorithm is summarized in Algorithm 1.

Algorithm 1 Low-Complexity IRLS-Based Compressive Spectrum Sensing Algorithm

Require: samples vector $\boldsymbol{y} \in \mathbb{R}^N$, measurement matrix $\boldsymbol{\Phi} \in \mathbb{R}^{M \times N}$, initial value $\Omega_\epsilon^{(0)}$, $\boldsymbol{W}^{(0)}$ and $\lambda(\boldsymbol{x}^{(0)})$.
Ensure: Practical solution $\boldsymbol{x}^*$

for $l = 1, \cdots, l_{\max}$ **do**
  Update: $\boldsymbol{H} = \boldsymbol{\Phi}^t \boldsymbol{\Phi} + \lambda(\boldsymbol{x}^{(l-1)}) * \boldsymbol{W}^{(l-1)}$
  Update: $\boldsymbol{P}^{-1} = (\overline{\boldsymbol{\Phi}^t \boldsymbol{\Phi}} * \boldsymbol{I} + \lambda(\boldsymbol{x}^{(l-1)}) * \boldsymbol{W}^{(l-1)})^{-1}$
  Update $\boldsymbol{x}^{(l)}$ with the inverse of preconditioner $\boldsymbol{P}^{-1}$
  Regularizer update:
   if $||\Delta \boldsymbol{x}^{(l)}|| \le \frac{\epsilon^\nu}{100}$: $\Omega_\epsilon^{(l)} = \left(1 + \frac{e^{-2l}}{h(\boldsymbol{x}^{(l)})_{k+1}}\right) h(\boldsymbol{x}^{(l)})_{k+1}$
   else: $\Omega_\epsilon^{(l)} = \Omega_\epsilon^{(l-1)}$
  Weights update: $\boldsymbol{w}^{(l)} = \left((x_i^{(l)})^2 + \Omega_\epsilon^{(l)}\right)^{\frac{\nu}{2}-1}$
  Penalty parameter update:
   $\lambda(\boldsymbol{x}^{(l)}) = \frac{1}{2}||\boldsymbol{\Phi x}^{(l)} - \boldsymbol{y}||_2^2 / [\varrho - \sum_{i=1}^{N} w_i^{(l)} (x_i^{(l)})^2]$
end for
return $\boldsymbol{x}^* = \boldsymbol{x}^{(l+1)}$.

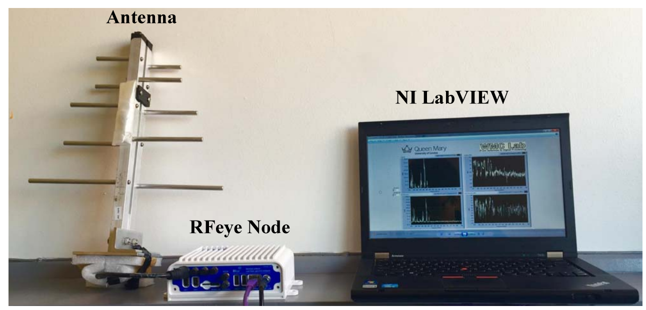

Fig. 1. Experimental setup for real-time processing and live compressive spectrum sensing testbed on TVWS [6].

IV. Experimental Results

Consider the simulated wideband signal $x(t) \in \mathcal{F} = [0, 500]$ MHz, whose DFT is denoted as $\boldsymbol{x}_0^{\text{sim}}$ which contains up to k

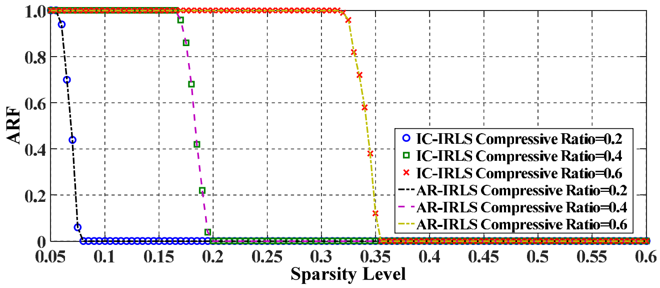

Fig. 2. ARF vs. sparsity level between the proposed IC-IRLS algorithm and AR-IRLS algorithm with simulated signals under different compressive ratios = 0.2, 0.4, 0.6.

active channels: $x(t) = \sum_{i=1}^{k} \sqrt{E_i B_i}\text{sinc}(B_i(t-t_i))e^{j2\pi f_i t} + n(t)$, where $\text{sinc}(x) = \sin(\pi x)/(\pi x)$, E_i, t_i and f_i represent the energy, the time offset, and the central frequency of the i-th sub-band and $n(t)$ denotes the noise. The i-th sub-band covers the frequency range $[f_i - \frac{B_i}{2}, f_i + \frac{B_i}{2}]$. To demonstrate the effectiveness of the proposed algorithm over the wide-band spectrum with the varying bandwidths and power levels of primary signals, the bandwidths B_i of i-th primary signal is varying and the corresponding central frequency f_i is randomly located in $[\frac{B_i}{2}, W - \frac{B_i}{2}]$. The total sensing time is T, and thus the number of samples collected by the Nyquist sampling rate could be calculated as $N = T \cdot f_{NYQ}$. Rather than using the Nyquist sampling rate $f_{NYQ} \geq 2W = 1000$ MHz, we adopt the sub-Nyquist sampling rate $f_s < 2W$ which is depended on the maximum sparsity level $k_{\max}$ that can be estimated by long-term spectral observations. As shown in Fig. 1, the real-world signal $\boldsymbol{x}_0^{\text{real}}$ is collected by the real-time wideband compressive spectrum sensing testbed based on the RFeye node, which is an intelligent spectrum monitoring system that can provide real-time 24/7 monitoring of the radio spectrum. The frequency of the received real-world TVWS signal ranges from 470 to 790 MHz and the channel bandwidth is 8 MHz in Europe. The setting is consistent with the current bandwidth used in TV broadcasting. Therefore, the total bandwidth of the real-world signals is 320MHz. To quantify the reconstruction performance of the proposed algorithm, we calculate the acceptable reconstruction frequencies (ARF) based on the conventional relative mean square error (r-MSE): $||\boldsymbol{x}^* - \boldsymbol{x}_0||/||\boldsymbol{x}_0||$, where $\boldsymbol{x}_0 = \boldsymbol{x}_0^{\text{sim}}$ and $\boldsymbol{x}_0 = \boldsymbol{x}_0^{\text{real}}$ for simulated signal and real-world signal respectively, which is defined as the case with r-MSE $\leq 10^{-2}$. We also compare the convergence speed if the proposed algorithm (termed IC-IRLS) with that of the conventional AR-IRLS algorithm (termed AR-IRLS) [6] and regularized IRLS algorithm [3] (termed Reg-IRLS) in terms of iterations.

Firstly, we demonstrate that the reconstruction performance is not degraded with the reduced computational complexity of the proposed algorithm by plotting the ARF against the sparsity level ranging from 0.05 to 0.60 under compressive ratios = 0.2, 0.4, 0.6 for both the proposed IC-IRLS and AR-IRLS in Fig. 2. It can be seen that the signal reconstruction of the proposed IC-IRLS algorithm has high fidelity guarantee as same as the AR-IRLS algorithm under different compression ratios. Secondly, to validate the effectiveness of the proposed algorithm in real-time processing with real-world signals as well as to prove that the reduced computational complexity in the proposed algorithm from cubic time to linear is not achieved at the cost of more iterations, we compare the number of iterations of the proposed algorithm with the AR-IRLS algorithm and the regularized IRLS algorithm under the compressive ratio = 0.52 in Fig. 3, where the sparsity level of the received real-world signal is about 0.2. It can be observed that the proposed algorithm holds fast convergence rate, which achieves the 100% successful reconstruction of the real-world signals when the number of iterations is 9 without introducing any prior information, where the conventional IRLS algorithms require at least 34 iterations to achieve the same performance. Therefore, the proposed algorithm keeps the fast convergence speed with significantly reduced computational complexity.

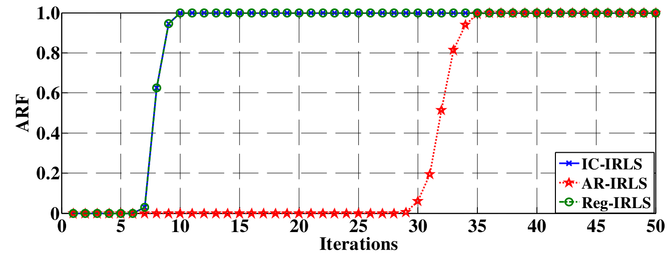

Fig. 3. ARF vs. iterations between the proposed IC-IRLS algorithm and conventional IRLS algorithms with real-world signals, where the sparsity level of the received real-world signal is about 0.2 and compressive ratio = 0.52.

V. Conclusion

In this letter, we have proposed a low-complexity compressive spectrum sensing algorithm which reduces the computational complexity from cubic time to linear time with high fidelity guarantee and fast convergence rate. The proposed algorithm was tested over not only the simulated signals but also the real-world signals. The numerical and experimental results have demonstrated that the proposed algorithm can achieve the fast convergence speed and keep the same accurate signal reconstruction with reduced computational complexity.

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