Research Article

Cooperative Spectrum Sensing Algorithm Based on CS-SLIM Iterative Minimization Sparse Learning

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Dynamic spectrum management is a key technology in cognitive wireless sensor network (C-WSN), in which spectrum sensing plays an important role. In this paper, we propose an improved approach as sparse learning via iterative minimization based on compressive sampling (CS-SLIM) for wideband spectrum detection. CS-SLIM can provide wideband spectrum detection with almost the same accuracy but a lower computational burden than that of SLIM. The measurement matrix and the computational complexity for CS-SLIM are discussed. Means squared errors (MSEs) at various measurement samples are provided to demonstrate the performance of the proposed approach in sparse scenes. It is also proved that the algorithm is suitable for sparse signal reconstruction and wideband spectrum sensing in C-WSN.

1. Introduction

Dynamic spectrum management is a key technology in cognitive radio. In cognitive wireless sensor network (C-WSN), the first step of dynamic spectrum management is spectrum sensing, which is a task for obtaining awareness about the spectrum usage and existence of primary users (PUs) that contains a large amount of sensors, which have cognition functions [1]. Cognitive WSN sensors use the spectrum holes of PUs to transmit their local sensing information, which gathers the local results in order to realize data fusion and reconstruct the sensing information collected by all sensors [2]. One way of doing spectrum sensing is energy detection [3]. However, traditional energy detection consumes a lot of resources and for cognitive sensor networks, sensing may be applied to the local results to save resource and to improve efficiency [4, 5]. Nevertheless, spectrum sensing in C-WSN could be regarded as a challenging task due to the wide frequency bandwidth.

Compressed sampling (CS) theory provides an efficient way to sense sparse or compressible signals. The characteristics of discrete-time sparse signal can be completely captured and represented by a number of projections over a random basis and reconstructed perfectly from these random projections. An intriguing aspect of the theory is the central role played by randomization that preserves the structure of the signal and the original signal reconstruction is conducted using an optimization algorithm from these projections, while reconstruction algorithm design with low mean-square errors (MSE) is regarded as the key issue for practical application of CS theory in large-scale distributed WSN. CS can be implemented as a framework to reduce the spectrum sensing rate in C-WSN. For sparse input signals, analog-to-information conversion (AIC) promises greatly reduced digital data rates (matching the information rate of the signal), and it offers the ability to focus only on the relevant information.

In this paper, after compressive sampling, signals can be exactly recovered with high probability by using effective sparse signal reconstruction algorithms. The present sparse signal reconstruction algorithms can be divided into two categories. One is convex optimization algorithm such as basis pursuit (BP) [6]. The other is greedy algorithm including Matching Pursuit (MP) [7], Orthogonal Matching Pursuit (OMP) [8], and Compressive Sampling Matching Pursuit (CoSaMP) [9]. Compared with greedy algorithm, convex optimization algorithm has higher estimation accuracy while the former has lower computational burden. In particular,
sparse learning via iterative minimization (SLIM) [10] algorithm follows an \( \ell_q \)-norm constraint (for \( 0 < q \leq 1 \)) and can provide more accurate estimation at lower computational burden than many \( \ell_1 \)-norm-based approaches which are mentioned before. So SLIM is a relatively good sparse signal reconstruction recovery algorithm. But SLIM uses Bayesian information criterion (BIC) to determine \( q \) automatically through match cycling, leading to a high computational complexity.

Cooperative wideband spectrum sensing in C-WSN has high requirements for the accuracy of spectrum reconstruction, the algorithm complexity of the system, and the corresponding computing time. However, the present sparse signal reconstruction algorithms cannot meet all of the requirements. This paper put forward a cooperative spectrum sensing algorithm that identified sparse learning via iterative minimization based on compressive sampling (CS-SLIM). The algorithm combines SLIM and compressive sampling theory together. With the guarantee of an accurate reconstruction of sparse signal frequency spectrum, it also reduces signal sampling frequency and decreases data size to the greatest degree. Therefore, it reduces the complexity of the system, saves computing time, and realizes dynamic allocation of the idle channels with the premise of not interfering in the communication among PUs. Compared with cooperative spectrum sensing algorithm based on \( \ell_1 \)-norm, the algorithm based on CS-SLIM proposed in this paper has a higher accuracy of the signal spectrum reconstruction and a lower systemic complexity in the condition of C-WSN when there is white Gaussian noise in the information channels. So the computing time is saved and the requirement is better met for dynamic spectrum management with the premise of not interfering in the communication among PUs to improve spectrum utilization and network performance. Signal models are introduced in Section 2 and compressive sampling models in Section 3. Section 4 proposes cooperative frequency spectrum sensing algorithm based on CS-SLIM including CS-SLIM reconstruction algorithm and cooperative spectrum sensing algorithm. In Section 5, simulation experiment and simulation analysis are presented. Finally, conclusions are drawn in Section 6.

2. System Model

Suppose that an authorized user (also known as PU) and many unauthorized users (also known as cognitive radio user, CR) distribute in a certain area. In this paper, we use 4 CR users to do cooperative spectrum sensing, as shown in Figure 1. The communication between PUs only occupies a small part of the authorized spectrum, while most of the authorized spectrum is idle. In other words, the occupied spectrum is sparse compared with the authorized spectrum. So CR users use sparse signal reconstruction algorithm to reconstruct the spectrum; then they do the spectrum sensing. The result is sent to the data fusion center to do cooperative spectrum sensing. Data fusion center will feed back the result that whether the subchannel is idle to CR users to manage dynamic spectrum for the communication among CR users.

Figure 2 describes the compression spectrum sensing system scheme for a CR user. The broadband analog signal received by CR users is compressively sampled through analog-to-information conversion (AIC) system. The compressed spectrum signal is exactly reconstructed by sparse signal reconstruction algorithm to do the spectrum sensing using energy detection (ED) for one CR user.

The output signal of AIC is

\[
    r(m) = \int_0^T y(t) \, p_c(t) \, h(m\mu - t) \, dt, \quad (1)
\]

where \( y(t) \) is the broadband analog signal received by CR user, \( p_c(t) \) is a pseudorandom maximal-length PN sequence of \( \pm 1 \)'s, \( h(m\mu - t) \) is impulse response of a low-pass filter, \( m \) is the row of \( r(m) \), \( \mu \) is the sample rate of ADC, and \( T \) is the spectrum sensing method for one CR user.

In [11], \( y(t) \) is defined in frequency domain as

\[
    y(t) = \sum_{n=1}^{N} a_n \phi_n(t) + e(t), \quad (2)
\]

where \( \phi_n(t) \) is Fourier basis function, \( a_n \) is the coefficient of the \( n \)th basis function, and \( e(t) \) is additive noise.

The bandwidth of \( y(t) \) is \( W \). The signal can be divided into \( L \) nonoverlapping narrow bands in the frequency domain; in other words, bandwidth of the wideband signal is divided into \( L \) subchannels. Due to the low use ratio of the PU spectrum, the signal is sparse in frequency. Namely, assume that PUs continuously occupy minority subchannels to transmit signal. Define \( y \in \mathbb{R}^N \) as the discrete-time form of analog signal \( y(t) \), where \( N \) is Nyquist rate. The time-domain signal
3. Compressed Sampling Model

The compressible or sparse signal is compressed and sampled using the theory of CS, based on which the signal is recovered with high probability by sparse signal reconstruction algorithms. This approach is proved to be feasible. In [9], a K-sparse signal x of length N could be recovered accurately from the M-dimensional received signal y by combining the theory of CS with an $\ell_1$-optimization algorithm.

We assume that y is a received signal sampled by traditional sampling approach and it can be given by

$$y = \Psi x,$$

where $\Psi$ is basis matrix and y is the signal vector. In this paper, we consider the additive noise e in the received signal y and let $\Psi = F_N^{-1}$. Therefore, replace $\gamma(t)$ in (1) with (2) and then the simplified form can be expressed as

$$y = F_N^{-1}x + e.$$

The received signal y is compressed and sampled through the theory of CS using a measurement matrix with low dimension to obtain the $M_{CS}$ ($M_{CS} < N$) measurement signal r. Consequently, the dimension is decreased as

$$r = \Phi y = \Phi \left( F_N^{-1}x + e \right) = \Theta x + \bar{e},$$

where $\Theta = \Phi \Psi \Phi F_N^{-1}$ is the $M_{CS} \times N$ sensing matrix and $\Phi$ represents a $M_{CS} \times N$ measurement matrix. The original signal x can be calculated through (6). So r compressed by CS is used in sparse signal recovery algorithms to recover the original signal.

4. Cooperative Spectrum Sensing

4.1. Sparse Reconstruction Algorithm Based on CS-SLIM

SLIM is a regularized minimization approach with an $\ell_q$-norm ($0 < q \leq 1$) constraint and can also be regarded as a natural extension to $\ell_1$-norm-based approaches. Reference [10] demonstrates that compared with many existing sparse signal reconstruction algorithms including IAA [12], SLIM has remarkably lower computational burden by incorporating the conjugate gradient least squares (CGLS) approach. The user parameter q is determined automatically by using the Bayesian information criterion (BIC) in SLIM. And [10] has also demonstrated that SLIM approach offers more accurate estimates than many $\ell_1$-norm-based approaches and greedy algorithms.

Consider the regularized minimization algorithm for sparse signal recovery as

$$(\hat{x}, \hat{\eta}) = \min_{x, \eta} g_q(x, \eta),$$

where

$$g_q(x, \eta) = M \log \eta + \frac{1}{\eta} \| y - Ax \|^2_2 + \sum_{n=1}^{N} \left( \| x_n \|^q - 1 \right),$$

and $\eta$ represents the noise power. This approach is called sparse learning via iterative minimization. The first part of $g_q(x, \eta)$ is a fitting term and the other part is a penalty term. The penalty term becomes $2\|x\|_1 - 2\Omega$, which is close to $\ell_1$-norm constraint when $q = 1$. We note that when $q \to 0$, the penalty term is not $\ell_1$-norm constraint approach but is $2\sum_{n=1}^{N} \log |x_n|$, which promotes the sparsity when $x_n \to 0$, $\log |x_n| \to -\infty$. The user parameter q is determined automatically by BIC [10] as

$$\text{BIC}_q = 2M_r (L + N_r - 1) \times \log \| y - \tilde{A} \tilde{x} \|^2_2 + 5h(q) \times \ln (2M_r (L + N_r - 1)).$$

We assume that initial estimation of $x$ and $\eta$ is offered. The optimal value of $x$ and $\eta$ is gained by a cyclic optimization technique. We iterate between two steps: optimizing $x$ by minimizing $g_q(x, \eta)$ with $\eta$ fixed and optimizing $\eta$ by minimizing $g_q(x, \eta)$ with x fixed. So the $(t + 1)$th iteration of x and $\eta$ is obtained as [12]

$$x^{(t+1)} = \Phi^H \left( \tilde{A} \Phi^H (\tilde{A} \Phi^H + \eta^{(t)} I)^{-1} y \right),$$

$$\eta^{(t+1)} = \frac{1}{M} \| y - \tilde{A} x^{(t+1)} \|^2_2.$$
(3) Choose optimal measurement matrix by the simulation of MSE and compress received signal y to measurement signal r by applying the theory of CS.

(4) Initialize the parameters of SLIM with y replaced by r.

(5) Assume that \( x^t \) and \( \eta^t \) in the tth iteration have been obtained. Thus the \( x^{(t+1)} \) and \( \eta^{(t+1)} \) in (t + 1)th iteration are gained by iterative rule of SLIM approach until the 15th iteration time or the stop criterion is satisfied:

\[
\frac{\|x^{(0)} - x^{(t-1)}\|_2}{\|x^{(0)}\|_2} < \Delta,
\]

where \( \Delta \) is a small positive number.

4.2. Cooperative Spectrum Sensing. Because there is instability in spectrum sensing of a CR user, this paper conducts cooperative spectrum sensing aiming at several CR users. Presume that the observation conditions of several CR users are independent identically distributed with the same SNR. Each CR user carries out independent detection for the first subchannel and gets jth independent sensing result \( T_{j,l} \), \( l = 1, 2, \ldots, L \), \( j = 1, 2, \ldots, J \). All of these are collected in the fusion center. Then the final judgment about whether this channel is idle is made.

Each CR user uses energy detection (ED) method when detecting independently a certain subchannel. So the decision of the lth subchannel is now defined as

\[
\hat{d}_l = \begin{cases} 1 & \xi_l \geq \eta, \\ 0 & \text{otherwise}, \end{cases}
\]

where \( \eta \) is an appropriate threshold with ED. When \( \hat{d}_l = 1 \), it shows that the lth subchannel is now occupied by PU, and \( \hat{d}_l = 0 \) means the lth subchannel is idle, and where \( 0 = f_0 < f_1 < \cdots < f_L \) is the frequency domain boundary of L subchannels,

\[
T_{l,j} = \frac{1}{f_l - f_{l-1}} \sum_{i=f_{l-1}}^{f_l} |\hat{x}(i)|^2, \quad l = 1, 2, \ldots, L.
\]

We can use detection probability \( P_D \) and false-alarm probability \( P_F \) of the signals to evaluate the detection performance of the proposed method:

\[
P_D = \frac{d^T \hat{d}}{1^T \hat{d}},
\]

\[
P_F = \frac{(1 - d)^T \hat{d}}{L - 1^T \hat{d}}.
\]

Here the binary vector \( d \) with a length of \( L \) shows PUs’ real occupation frequency; 1 indicates a vector with all ones of \( L \).

There are two kinds of decision rules of the data fusion center: hard decision and soft decision. Hard decision includes “and” decision, “or” decision, and “K” decision, while soft decision includes maximum ratio combining decision, equal gain combining decision, and selection combining decision. In order to make sure that the communication among PUs is not interfered with greatest degree, we choose “or” decision and also equal gain combining decision to simplify models.

(1) “Or” Decision. “Or” decision means that as one CR user believes this subchannel is occupied by PUs, it is judged that this channel is occupied. Therefore, it can be guaranteed to the greatest degree that the communication among PUs, in other words, maximizes the cooperative detection probability \( P_D \). So the cooperative detection probability of the lth channel is \( Q_{P_D} = \max(T_{l,1}, T_{l,2}, \ldots, T_{l,J}) > \eta \).

(2) Equal Gain Combining Decision. Equal gain combining decision means the fusion center receives the detection information from \( J \)th CR users, so the new fusion detection measurement \( T_l = \sum_{j=1}^{J} c_j T_{l,j} \) of the lth channel is created, where \( c_j = 1/J \) is the weight of the \( j \)th CR user. So the cooperative detection probability of the lth channel is \( Q_{P_D} = P(T_l > \eta) \).

5. Numerical Results and Analysis

It is the presence of a PU and several CR users in a certain area which shares a broadband with a total bandwidth of 128 MHz, and this broadband is divided into 16 subchannels with equiband. Suppose that the PU occupies some of the subchannels randomly and continuously with an average subchannel occupation rate of 25%. We choose 4 CR users to conduct cooperative spectrum sensing, and all of the 4 users keep silence during the monitor period. Suppose that the SNR of the 4 cooperative CR users in the simulation condition varies from 10 dB to 30 dB.

One sees that the signal frequency spectrum can be reconstructed with high probability, while NMSE drops gradually with the increase of the compression ratio and the SNR. Meanwhile, as the sampling number increases, the detection probability increases rapidly until up to one. However, the computing time also increases which is smaller compared with the other algorithm.

Figure 3 shows the reconstruction signal frequency spectrum figure when the received signal is polluted by white Gaussian noise, with an SNR of 20 dB and a compression ratio of 0.5. It can be seen from the figure that when there is white Gaussian noise, CS-SLIM can still reconstruct the signal spectrum with high precision.

To detect the performance of CS-SLIM more accurately, we introduce NMSE, which is

\[
\text{NMSE} = \frac{1}{K} \sum_{k=1}^{K} \frac{\|x_k - \hat{x}_k\|_2}{\|x_k\|_2},
\]

where \( x_k \) is the original signal spectrum of the kth experiment and \( \hat{x}_k \) is the reconstructive signal spectrum of the kth experiment. Figure 4 shows the relationship between NMSE and SNR when compression rate is 0.8. It can be seen from the figure that as SNR increases, NMSE decreases continually. Figure 5 presents the curve of the NMSE with the increasing of compression rate when SNR is 20 dB. As Figure 5 shows,
as the compression rate increases, the NMSE curve of the CS-SLIM algorithm drops gradually and the reconstruction quality of the signal spectrum is improved too.

Figure 6 shows the variation tendency with the change of compression rate of the detection probability of the cooperative spectrum sensing algorithms which are based on CS-SLIM, and this probability is adjudged, respectively, by “or” principle and equal gain combining decision. One sees that when the sampling number increases, the detection probability increases too. When the compression rate is larger than 0.35, the detection probability of the cooperative spectrum sensing algorithms based on CS-SLIM which are adjudged by “or” principle is 1. When the compression rate is larger than 0.6, the detection probability of the cooperative spectrum sensing algorithms based on CS-SLIM which are adjudged by “equal gain combining decision” principle is 1. It means that when compression rate is larger than 0.6, the cooperative spectrum sensing algorithms based on CS-SLIM which are adjudged by “or” principle and “equal gain combining decision” can both differentiate between idle subchannels and busy subchannels. The performance of the two different cooperative spectrum sensing methods which use “or” principle is better than that when using “equal gain combining decision” principle but the detection probability can both reach 1 when there is smaller compression rate.

We could know that the algorithm proposed in [14] has better performing and also more time consuming while
its computing time is four times that of the standard $\ell_2/\ell_1$-norm minimization. But the algorithm based on $\ell_1$-norm minimization has better performance and also lower computational complexity compared with $\ell_4$ and $\ell_2$-norm minimization. SLIM uses the conventional Nyquist sampling theorem while CS-SLIM uses AIC, the sampling rate of which is much smaller than the Nyquist sampling rate. So the data size and the computation complexity are reduced and the computation time is saved a lot. Figure 3 has shown that the frequency spectrum can be reconstructed accurately when compression ratio is 0.5. The computational times needed by SLIM and CS-SLIM are 1.97 and 1.35 s (when compression ratio is 0.5), respectively (an ordinary PC with an Intel Core 2 Duo 2.20 GHz CPU was used). The computational time of CS-SLIM is saved by almost 32% compared to SLIM.

6. Conclusions

This paper introduces the cooperative spectrum sensing and compression sensing theory in the broadband cognitive wireless sensor network. A novel cooperative spectrum sensing algorithm is proposed in this paper which is cooperative spectrum sensing algorithm using sparse learning via iterative minimization based on compressive sampling. In cooperative spectrum sensing, the key role is sparse signal spectrum reconstruction algorithm. The simulation experiment result shows that as the cooperative spectrum sensing algorithm introduced in this paper precisely reconstructs the signal spectrum, reduces the complexity of the system greatly, and saves a lot of computing time. Therefore, it can better allocate the idle subchannels dynamically with the premise of not interfering in the communication among the PUs and improving spectrum utilization. From the numerical results it can be seen that the cooperative spectrum sensing algorithm based on CS-SLIM achieves the expected result and proves its relatively high spectrum reconstruction precision and low computing complexity.

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