Wideband spectrum sensing using low-power IoT device

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***Abstract*—We consider a compressive wideband spectrum sensing for low-power IoT devices as secondary users(SUs). We present the proposed scheme for cost-effective compressive sensing for wideband spectrum sensing with a large number of distributed SUs. SUs have a single RF-chain for the compressive sensing and the measurement samples obtained at each SU are sent to the fusion center. The fusion center performs the proposed algorithm which estimates the minimum measurement samples for the reconstruction process. Among the total measurement samples by SUs, the rest of the samples except for the minimum number of samples are used for cooperative spectrum sensing. The original signal vector with the minimum measurement samples is reconstructed and cooperative gain is obtained by using the remainder of measurement samples effectively. We compare the performance of the proposed algorithm with the conventional compressive sensing scheme and the result shows that the proposed algorithm has better performance specially at the high sparsity order region.**

***Index Terms*—Compressive sensing, Wideband spectrum sensing, Sparsity order estimation, Signal recovery**

I. Introduction

As wireless communication traffic increases, the problem of insufficient frequency resources becomes more and more, and cognitive radio technology, a frequency sharing technology, has emerged. Cognitive radio has been proposed to effectively use the frequency spectrum used by primary users(PUs) with low efficiency. Spectrum sensing and dynamic spectrum access are required as essential techniques in order for Secondary Users(SUs) to effectively use license bands without interfering with PUs. The spectrum sensing process is the first step that the SU needs to perform in order to detect whether the user is within the license band frequency. How accurately the SU detects the PU is the most important and essential process because it significantly affects the performance of the SU network and interference on the PU network. For this reason, a variety of spectrum sensing methods have been extensively studied among the fields of cognitive radio research [1]. In particular, as the frequency band of interest increases, the opportunity to use the frequency increases, leading to more research on wideband spectrum sensing.

Wideband spectrum sensing is a technique that detects spectrum of frequency bandwidth that exceeds the coherence bandwidth of the channel. Among various wideband spectrum sensing methods, compressive sensing has been in the spotlight in the research field [2] [3], Since this approach mitigates high sampling rates, high computational complexity, and hardware cost issues. According to the compressive sensing theory, a signal having a sparse characteristic in a certain domain can be compressed with the far less number of measurement samples and correctly reconstructed to the original signal. Given a K-sparse signal x of length N, the minimum number of measurement samples for some constant $c > 0$ is well known as $M \geq cKlog(N/K)$. In the wireless communication channel environment, the sparsity order of frequency spectrum changes over time. Therefore the degree of sparseness of the spectrum cannot be known until the spectrum is sensed. As a result, it is difficult to know the minimum number of measurement samples required for the compressive sensing. For this reason, the majority of studies of wideband spectrum sensing algorithms with compression sensing use the maximum sparsity order obtained from the statistical characteristic of the frequency spectrum. The reconstruction can be correctly performed with the sufficient number of measurement samples set by the maximum sparsity order in advance. However, in the case of sensing a spectrum with low sparsity, the inefficiency of acquiring more samples arises even though it can be reconstructed with a small number of samples. Hence, estimating the sparsity order or estimating the minimum number of measurement samples should be considered an essential process for cost-effectively performing compressive sensing for wideband spectrum [5]. In order for low-power IoT devices to use spectrum as SUs, low hardware cost and power-efficient system configuration are required. In this paper, we propose algorithms that performs compressive sensing by multiple low-power IoT devices with a single RF-chain, and performs cooperative reconstruction with the minimum number of samples obtained by the proposed minimum measurement sample estimation algorithm.

The rest of the paper is organized as follows. In Section II, the basic concept of CS is reviewed. We describe the system model briefly and the proposed algorithm is covered in Section III. Simulation results and analysis are then presented in Section IV. Finally, we conclude in Section V.

II. Compressive sensing

Compressive sensing is a method to compress a original signal with a sparse characteristic in a certain domain to much fewer samples and reconstruct to the original signal [4] [6]. Assume that there are a signal vector s and a measurement matrix Φ, then the $M \times 1$ measurement vector y can be represented as

$$y = \Phi s \tag{1}$$

where the $N \times 1$ vector s is a sparse signal with $K \ll N$ non-zero elements and the measurement matrix Φ is a $M \times N$ matrix. The compressive sensing theory states that a signal can be recovered from $M \geq cKlog(N/K)$ measurements for some constant $c > 0$, provided the signal has the sparsity order of K [7]. If the signal is not sparse, the signal can be considered as a sparse signal in a certain domain through the $N \times N$ sparsity basis matrix Ψ. The elements of the measurement matrix can be composed of random elements such as Gaussian or Bernoulli random distribution. The measurement vector y can be rewritten as

$$y = \Phi x = \Phi \Psi s \tag{2}$$

If the size of the measurement vector y is greater than the minimum number M determined by N and K, then reconstruction is correctly performed by solving the following l_1-norm optimization problem [4] [6]

$$\hat{s} = \arg\min_{s} \parallel s \parallel_1 \quad s.t. \quad y = \Phi \Psi s \tag{3}$$

III. System model & The proposed algorithm

A. System Model

We consider a SU network comprising of L SUs which have a single RF chain for compressive sensing and a centralized fusion center. The number of SUs, L, is assumed sufficiently larger than the minimum required measurement samples for the reconstruction, M ($L \gg M$). The frequency range of interest consists of N non-overlapping channels and PUs occupy only a small portion of the channels at each instance of time. Each SU performs compressive sensing periodically, and the measurement samples acquired by compressive sensing are sent to the fusion center. Subsequently, the collected measurement samples are cooperatively reconstructed to the original signal through the proposed algorithm at the fusion center and state of each channel slot is determined. Our proposed scheme consists of three steps as follows: 1) Compressive spectrum sensing at each SU and data fusion at the fusion center, 2) Minimum number of measurement samples estimation, 3) Cooperative spectrum state decision.

B. Compressive spectrum sensing at single SU and data fusion at the fusion center

Each of SU receiver $l, l = 1, ..., L$ collects time-domain samples y_l from the channel energy vector s. When the SU receivers obtains the measurement sample, a row vector $\{\phi_l\}_{l=1}^{L}$ of $L \times N$ measurement matrix Φ is used as a measurement vector. The sensing process that occurs at l-th SU is as follows

$$y_l = \phi_l F_N^{-1} s + w_l \tag{4}$$

Algorithm 1: Minimum number of measurement samples estimation

Input : $\rho_{thres}, M_{step}, y, \Phi$
Output : $\hat{M}$
for $i = M_{min}$ **to** L **do**
  $\hat{s}_i = \arg\min_{s} \parallel s \parallel_1 \quad s.t. \quad y_{1:i} = \Phi_{1:i} F^{-1} s$
  $\rho_i := maxE[\hat{s}_i(m+n)\hat{s}^*_{i-1}(n)]$
  if $\rho_i > \rho_{thres}$ **then**
    $\hat{M} := i$ stop iteration
  else
    $i := i + M_{step}$
  end if
end for
return $\hat{M}$

where the $M \times 1$ vector s is the channel energy vector and w_l is the white gaussian noise. F_N^{-1} denotes the N points inverse Fourier transformer. The measurement samples obtained by (4) are sent to the fusion center. We assume that the channel states between SUs and the fusion center are known to each other. The fused data at the fusion center can be written as follows

$$y = \Phi F_N^{-1} s + w \tag{5}$$

where $\Phi = [\phi_1^T, ..., \phi_l^T, ..., \phi_L^T]^T \in R^{L \times N}$

C. Minimum number of measurement samples estimation

Without knowing K, through the result of reconstructed sample values compare serially reconstructed vector and calculate correlation of reconstructed vectors M_{step} and ρ_{thres} are predetermined parameters for the algorithm

The minimum sparsity order K_{min} is known as prior information through the statistical characteristics of the spectrum. Based on the minimum sparsity order K_{min}, minimum required number of samples for reconstruction M_{min} can be achieved. M_{min} is used as the initial value for the Minimum number of measurement samples estimation algorithm. The channel energy vector s is reconstructed repeatedly by increasing the size of measurement sample vector $y_{1:i}$ and measurement matrix $\Phi_{1:i}$ by the predetermined parameter M_{step}, where $y_{1:i} = [y_1, ..., y_i]^T, \Phi_{1:i} = [\phi_1^T, ..., \phi_i^T]^T$. Original signal vectors obtained in each iteration process are used to calculate cross correlation and the cross correlation value ρ_i at i-th iteration is compared with the predetermined threshold value ρ_{thres} in every iteration. If ρ_i exceeds ρ_{thres}, the iteration stops and the minimum number of samples is set as i.

D. Cooperative spectrum state decision

With the minimum number of measurement samples, $\hat{M}$, which is obtained through Algorithm 1, the number of sets for the cooperative spectrum state decision, N_{coop}, is decided. The reconstruction of the original signal is performed sequentially for N_{coop} times with the measurement sample

Algorithm 2: Cooperative spectrum state decision

Input : $y, \Phi, \hat{M}, \gamma_{thres}$

Output : D

Initialization: $N_{coop} := \lfloor L/\hat{M} \rfloor$

for $j = 1$ **to** N_{coop} **do**

$$\hat{s}_j = \arg\min_{s} \| s \|_1 \quad s.t. \quad y_{(j-1)\hat{M}+1:j\hat{M}} = \Phi_{(j-1)\hat{M}+1:j\hat{M}} F^{-1} s$$

$$d_j(i) = \begin{cases} 1 & \hat{s}_j(i) \geq \gamma_{thres} \\ 0 & \text{otherwise} \end{cases}$$

end for

$$D(i) = \begin{cases} 1 & \sum_{j=1}^{N_{coop}} d_j(i) > 0, \quad \text{OR Rule} \\ 0 & \text{otherwise} \end{cases}$$

return D

vector $y_{(j-1)\hat{M}+1:j\hat{M}} = [y_{(j-1)\hat{M}+1}, ..., y_{j\hat{M}}]^T \in C^{\hat{M}\times 1}$ and the subset of the measurement matrix $\Phi_{(j-1)\hat{M}+1:j\hat{M}} = [\phi^T_{(j-1)\hat{M}+1}, ..., \phi^T_{j\hat{M}}]^T \in R^{\hat{M}\times N}$. After the reconstruction process, each element of the estimated original signal vector is compared with the predetermined threshold value γ_{thres}, making a bianry hard decision, and as a result, d_j is obtained. The $d_j(i)$ obtained by the j-th estimated original signal vector represents the state of the i-th slot in the spectrum. Finally, when N_{coop} number of binary decision vector d are obtained, the binary decision vectors are cooperatively fused as D by a fusion rule. In this paper, we applied OR rule for the algorithm as an example.

IV. Simulation and Analysis

In this section, we present the performance comparison of the proposed widebnad spectrum sensing algorithm with the conventional wideband compressive sensing algorithm. In the simulation, We consider wideband of frequency spectrum which is separated into 1024 non-overlapping sub-channels and $L = 300$ distributed SUs. PUs randomly use the sub-channels according to the sparsity order. The performance metrics of interest are detection probability P_d and false alarm probability P_f. We evaluated the probability of detection P_d with a different sparsity order at a fixed false alarm probability, $P_f = 0.1$. The signal to noise ratio was also fixed to 10dB in the simulation. As the Fig.1 illustrates the proposed scheme has much better performance for high sparse frequency spectrum. In the proposed technique, the cross-correlation values are obtained using sequentially reconstructed original signal vectors, thereby determining the minimum number of samples. For this reason, the lower the correlation threshold ρ_{thres} is, the smaller the minimum number of samples tends to be estimated. Although it shows the proposed scheme has a slightly low performance in the low sparsity region, it represents high performance through cooperative gain and spatial diversity gain in general.

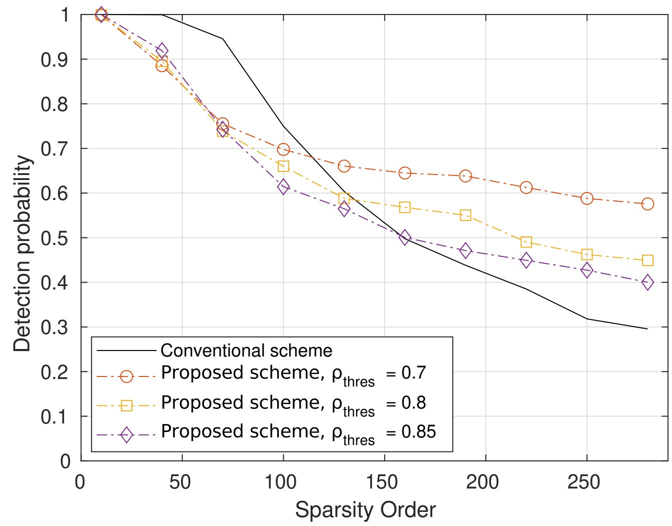

Fig. 1. Detection probability versus K, the number of nonzero element in the original signal vector s.

V. Conclusion

We proposed a cooperative compressive spectrum sensing scheme specially for low-power IoT devices. The proposed scheme estimates the minimum measurement samples and the samples exceeding the minimum number of samples were used for cooperative spectrum sensing. We presented the performance of the proposed scheme has better performance by spatial diversity at high sparsity order region.

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