Reconstruction Failure Detection for Wideband Spectrum Sensing with Modulated Wideband Converter Based Sub-Nyquist Sampling

Shilian Zheng[1,2] and Xiaoniu Yang[1,2]

[1]Science and Technology on Communication Information Security Control Laboratory, Jiaxing, China
lianshizheng@126.com, xiaonyang@126.com

[2]School of Telecommunications Engineering, Xidian University, Xi'an, China

Abstract

Modulated wideband converter (MWC) based sub-Nyquist sampling can be used for wideband spectrum sensing in cognitive radio networks. In this paper, a method is proposed for detecting whether the reconstruction process is unsuccessful due to non-sparse spectrum in MWC based wideband spectrum sensing to avoid causing harmful interference to primary users. The proposed method exploits the correlation between two consecutively recovered support sets. Simulation results show that the method can judge whether the reconstruction is successful or not with high probability. Compared with traditional spectrum sensing without reconstruction failure detection, the proposed method can lower the interference probability to primary users greatly when spectrum is not sparse.

1. Introduction

Cognitive radio is an emerging technology that can make efficient use of spectrum by opportunistically access the currently unused licensed spectrum, i.e., white spaces or spectrum holes [1]. As cognitive radios are secondary users of the spectrum, their functionality should not cause harmful interference to primary users. Since cognitive radios have no a prior knowledge on the spectrum usage information, they need to sense a wide spectral range to detect spectrum holes for communications. This process is known as wideband spectrum sensing, which is a key functionality of cognitive radio [2].

Some wideband spectrum sensing methods have been proposed in the literature, such as wavelet-based detection [3], multi-band joint detection [4], filter bank based method [5]. These methods are in the framework of Nyquist sampling. As wideband spectrum sensing needs to cover a wide frequency range, with Nyquist sampling, at least a sampling rate twice the frequency range is needed. A single commercial analog-to-digital converter (ADC) can not meet such a high sampling rate. The architecture with several sampling braches (each covers part of the frequency range) complicates the system design and implementation. Fortunately, the advance of compressed sensing [6] provides another way for wideband spectrum sensing which takes advantage of using sub-Nyquist sampling for signal acquisition [7-9].

Several sub-Nyquist sampling systems which have potential applications in wideband spectrum sensing have been proposed have been discussed in the literature. Modulated wideband converter (MWC) [10] is one of these sub-Nyquist sampling methods. In this paper, we focus on the MWC based sub-Nyquist sampling system. Using MWC based sub-Nyquist sampling for wideband spectrum sensing requires that the spectrum is sparse [9-11]. If the spectrum is not sparse, the reconstruction method can not provide a correct estimation of the original signal and "spectrum holes" detected based on this recovered signal may not be real spectrum white spaces. If cognitive radios access these "spectrum holes", they may cause harmful interference to primary users. As cognitive radio shave no a prior information on the activity of primary users, a mechanism is needed to detect spectrum non-sparsity. In [12], Zhang et al. proposed a collaborative non-sparsity protection scheme which exploited the correlation of Gaussian process (GP) model parameters obtained by several cooperative cognitive radios to detect the failure of compressed reconstruction owing to nonsparse spectrum. Their method needs several cognitive radios exchange information collaboratively. In this paper, we propose a method for detecting reconstruction failure which relies on a single cognitive radio. Our method exploits the correlation between two consecutively recovered support sets. We conduct simulations to validate this method.

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2. MWC-Based Sub-Nyquist Sampling

We assume the spectral range the cognitive radio needs to sense is $[0, f_e]$ which contains several narrowband primary signals with unknown frequencies. The Nyquist rate is $f_{\mathrm{NYQ}} = 2f_e$. In this paper we consider MWC as the sub-Nyquist sampling system for cognitive radios. MWC consists of an analog front-end with m branches. In the i th branch, the input signal is multiplied by a periodic waveform $p_i(t)$ with period T_p, filtered by a lowpass filter $h(t)$, and then sampled at rate $f_s = 1/T_s$, as shown in Fig. 1. For MWC, the following result holds [10]:

$$\mathbf{y}(f) = \mathbf{\Phi}\mathbf{z}(f), \qquad f \in [-f_s/2, f_s/2], \tag{1}$$

where $\mathbf{y}(f)$ is a vector of length m with i th ($1 \le i \le m$) element $y_i(f) = \sum_{n=-\infty}^{+\infty} y_i[n] e^{-j2\pi f n T_s}$, $\mathbf{z}(f)$ is an unknown vector of length $L = 2L_0 + 1$ with l th ($1 \le l \le 2L_0 + 1$) element $z_l(f) = X(f + (l - L_0 - 1)f_p)$, $f \in [-f_s/2, f_s/2]$, where $X(f)$ is the Fourier transform of the original signal $x(t)$, and $\mathbf{\Phi}$ is the observation matrix with elements $\phi_{il} = c_{i,L_0+1-l}$, $1 \le i \le m,\ 1 \le l \le 2L_0 + 1$, where $L_0 = \left\lceil \left(f_{\mathrm{NYQ}} + f_s\right)/2f_p \right\rceil - 1$, and $c_{il} = \frac{1}{T_p}\int_0^{T_p} p_i(t)\exp\left(-j2\pi lt/T_p\right)dt$. By solving (1), we can obtain the unknown $\mathbf{z}(f)$ ($f \in [-f_s/2, f_s/2]$) and thus recover the Fourier transform of the original signal $X(f)$. As $m < L$, problem (1) can be solved given that the unknown signal is sparse [10].

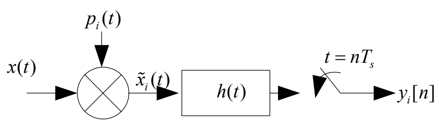

Figure 1. The *i*th branch of MWC.

3. Proposed Recovery Failure Detection Method for MWC Sub-Nyquist Sampling

After recovering $\mathbf{z}(f)$, wideband spectrum sensing can be performed as discussed in [9] or [11]. A requisition for MWC based compressed sensing is that the spectrum is sparse. If the spectrum is sparse, the recovery is successful and the wideband spectrum sensing result can be trusted. However, if the spectrum is not sparse, the recovery may fail. In this case, trusting spectrum sensing result may cause harmful interference to primary users. In this section, we propose a method for detecting whether the recovery is successful. Our method is based on the correlation of two consecutively recovered supports sets. It consists of the following four steps.

Step 1: Coarse support recovery. The first step is to find a coarse estimation of the support set $S = \{i \mid z_i(f) \ne 0\}$. A continuous-to-finite (CTF) block [10] is used to recover the support S. First, construct a matrix $\mathbf{Q} = \sum_{n=0}^{N-1} \mathbf{y}[n]\mathbf{y}^T[n]$, where $\mathbf{y}[n] = [y_1[n], y_2[n], ..., y_m[n]]^T$, and N is the number of samples used in each branch. Second, obtain $\mathbf{V}$ such that $\mathbf{Q} = \mathbf{V}\mathbf{V}^H$. Finally, solve the problem $\mathbf{V} = \mathbf{\Phi}\mathbf{U}$ to obtain the support of $\mathbf{U}$. It has been shown that the support of $\mathbf{U}$ is identical to S. In this paper, the recovery method used is orthogonal matching pursuit (OMP) [13]. We denoted the recovered coarse support as $\widehat{S}$.

Step 2: Support refinement. If the observation process of MWC is noiseless and the original signal is noiseless, the recovered support in Step 1 will be a correct estimation of the support of $\mathbf{z}(f)$. However, in spectrum sensing, the signal is usually corrupted by noise. The recovered support set may contain some noise subband. So in this step, we need to extract those noise subband from $\widehat{S}$. The subband signal can be obtained by $\mathbf{z}_{\widehat{S}}[n] = \mathbf{\Phi}_{\widehat{S}}^{\dagger}\mathbf{y}[n]$, where $\mathbf{\Phi}_{\widehat{S}}^{\dagger}$ is the (Moore-Penrose) pseudoinverse of $\mathbf{\Phi}_{\widehat{S}}$ and $\mathbf{z}_{\widehat{S}}[n]$ is a vector composed of all $z_l[n]$ ($l \in \widehat{S}$). $z_l[n]$ is the inverse-DTFT of $z_l(f)$. We apply energy detection to decide whether $z_l[n]$ is noise or not. We compute the energy of subband l as $E_l = \sum_{n=0}^{N-1} |z_l[n]|^2$. If $E_l < \eta$, subband l is judged to contain noise only and l is removed from $\widehat{S}$. η is a threshold.

Step 3: Support correlation computation. We use the correlation between two consecutively recovered support sets to decide whether the recovered results are trustable. We repeat step 1 and step 2 for two times by using consecutive samples (in total $2N$ samples) of $y_i[n]$ and obtain two recovered support sets which are denoted by $\widehat{S}_1$ and $\widehat{S}_2$ respectively. We assume that the spectrum environment changes slowly relative to the reconstruction process. If the spectrum is sparse and the recovery is successful, $\widehat{S}_1$ and $\widehat{S}_2$ would be highly correlated. However, if the spectrum is not sparse, the recovery will failed to provide a correct estimation of the support and $\widehat{S}_1$ and $\widehat{S}_2$ will differ from each other greatly. Fig. 2 illustrates an example. The compression ratio of MWC in this example is about 4.86. Fig. 2 (a) represents a sparse spectrum case while Fig. 2 (b) represents a non-sparse spectrum case. High correlation is observed when the spectrum is sparse. We compute the support correlation as $\xi = \left|\widehat{S}_1 \cap \widehat{S}_2\right| / \left|\widehat{S}_1 \cup \widehat{S}_2\right|$, where $\cap$ denotes intersection, $\cup$ denotes union, and $|P|$ computes number of elements in P. It's apparent that if $\widehat{S}_1 \approx \widehat{S}_2$, ξ is close to 1. If $\widehat{S}_1$ differs from $\widehat{S}_2$ greatly, ξ is close to 0.

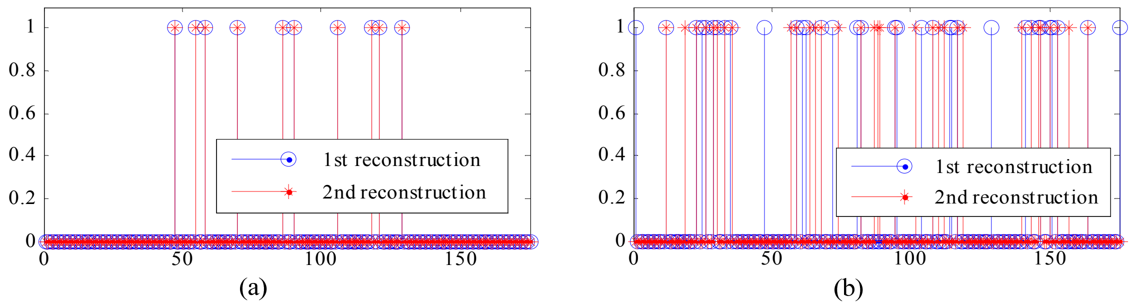

Figure 2. Recovered support sets. (a) Five out of 87 primary channels occupied, and (b) twenty out of 87 primary channels occupied.

Step 4: Decision. We use a threshold λ which is smaller than and close to one for reconstruction failure detection. If $\xi > \lambda$, we make the decision that the spectrum is sparse and the reconstruction process is successful. Otherwise, we consider the reconstruction process has failed. In this case, in order to protect primary users, the wideband spectrum sensing result will not be trusted and cognitive radio will not use any of those falsely discovered "spectrum holes".

4. Simulation Results

In the simulations, we assume that the spectral range is [0MHz, 525MHz] which is divided into 87 primary channels. Parameters for MWC are chose as follows: $f_s = f_p = 6$ MHz, $m = 36$. In this setting, the total sampling rate of the MWC is 216 MHz which is far less than the Nyquist rate 1.05 GHz. The primary signals are with either BPSK or QPSK modulation. The symbol rate takes one of the four choices: 1.5 ksps, 2 ksps, 2.5 ksps or 3 ksps. Raised cosine shaping filter is used. The signal to noise ratio (the sum of the power of the primary signals versus the noise power) is kept certain at 30 dB. η is chosen as the noise power multiplying the compression ratio. $\lambda = 0.9$.

Fig. 3 (a) shows the reconstruction success/failure verification rate of the proposed method. The reconstruction rate of OMP is illustrated for reference. Overall, the proposed method can judge whether the reconstruction is successful or not with high accuracy. As the proposed method relies on the correlation between two consecutively recovered support sets, in the areas where the reconstruction rate is around 1/2, the verification rate decreases slightly. Fig. 3 (b) illustrates the interference probability to primary users. It can be seen that with traditional method without

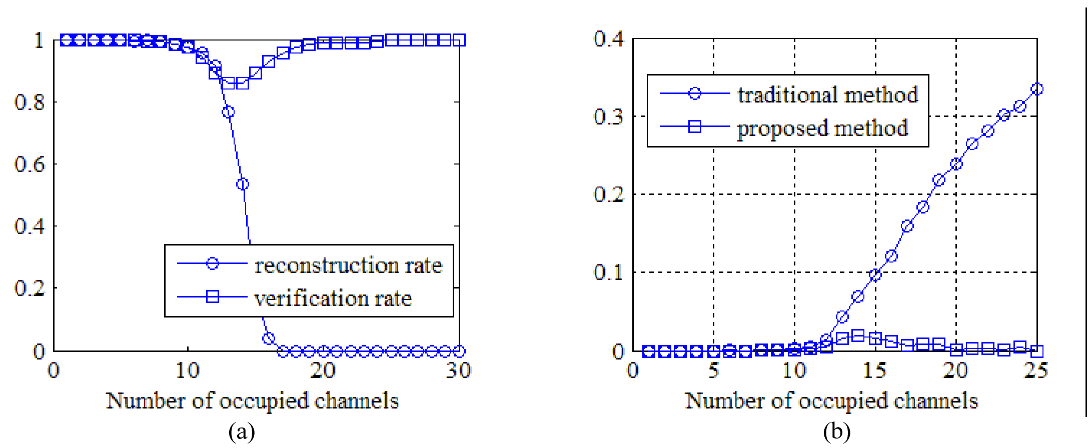

Figure 3. Simulation results. (a) Verification rate of the propose method, and (b) interference probability to primary users.

reconstruction failure detection, as the number of occupied channels increases, the interference probability to primary users increases. However, with our method, the interference probability keeps near zero when the spectrum is not sparse.

5. Conclusion

A method for detecting reconstruction failure due to non-sparse spectrum in MWC based sub-Nyquist sampling is proposed to avoid harmful interference to primary users. Simulations have shown that the proposed method can effectively judge whether the reconstruction process is successful or not and it can reduce the interference probability to primary user when the spectrum is not sparse. Performance in the sparsity area where the reconstruction rate is around 1/2 needs to be improved in the future work.

6. References

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