A Practical Implementation of TD-LTE and GSM signals identification via Compressed Sensing

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Abstract. Signal identification is a crucial subject in cognitive radio (CR) systems. In GSM spectrum refarming or spectrum monitoring scenarios, CR is required to identify on-the-air signals like long term evaluation (LTE), global system mobile (GSM). Second-order cyclostationary detection is an identification method robust to noise uncertainty and used widely in spectrum sensing. However, it requires high sampling rate and long processing time. In this paper, we first propose a compressed sensing (CS) based sampling structure to reduce the sampling rate using the second-order cyclostationary features of Time Division-LTE (TD-LTE) and GSM signals. Furthermore, an identification method for TD-LTE and GSM signals based on CS is employed to reduce sensing time. The performance of the method is evaluated by the practical on-the-air-signals measured with a spectrum analyzer. Numerical results show that our method can achieve a high detection probability with a low sampling complexity.

Keywords: Signal identification, compressed sensing, second-order cyclostationarity, TD-LTE, GSM

1 Introduction

Cognitive radio (CR) is an effective technology to tackle the spectrum scarcity problem. It allows secondary users to access the spectrum opportunistically without interfering with the primary users [1][2]. In some applications, in order to adapt to the complex radio environment, CR is required not only to identify the presence but also the type of on-the-air signals [3]. And in spectrum sharing scenario, such as GSM spectrum refarming for LTE co-channel deployments, it is more important to identify who is occupying the spectrum. And then corresponding decisions can be made to avoid interference with licensed users and improve spectrum sharing efficiency. Thus it is important for CR to identify LTE and GSM signals [4].

Second-order cyclostationary detection is one of the signal identification methods. It identifies different signals by detecting the second-order cyclostationary features related to frame structures, modulation, etc [5]. Since reference signals (RS) used for channel estimation and acquisition repeat every LTE frame, significant peaks are formed at certain fixed cyclic frequencies. This has been verified in [4] and [6] by acquiring the cyclic autocorrelation function (CAF). Second-order cyclostationary detection is robust to noise uncertainty and needs less prior information of the target signal. However, cyclostationarity based signal identification requires large signal samples and high computation complexity.

To reduce the complexity of second-order cyclostationary detection, compressed sensing techniques have been investigated in many studies [7]-[9]. Specifically, in [7], Tian proposed a compressive sampling scheme to recover a two dimensional cyclic spectrum in wideband sensing. However, this method relies on sparsity in both cyclic domain and frequency domain. In [8][9], the authors exploited the sparse feature of the CAF, upon which a CS based spectrum sensing method was proposed. This method shortens the sensing time and has a relatively low complexity. However, this method is only verified in the identification of simulated man-made narrow-band signals. So, real world experiments are needed to verify compressed sensing based signal identification using cyclostationary features. Different from the prior work on CS based cyclostationary identification, our paper evaluates the performance of the method by the measured on-the-air data. So our conclusions are more practical and can be used to guide piratical spectrum sharing deployments.

In our paper, we implement CS algorithm using real world TD-LTE and GSM signals acquired with a spectrum analyzer Tektronix 306B. The CAF of TD-LTE and GSM signals are obtained using the measured data and then the second-order cyclostationarity of the measured signals are verified for our proposed CS structure. Our contributions are as follows:
1.Using cyclostationary features, we are the first to propose a low-rate compressed sampling structure for TD-LTE and GSM signals identification.
2.Real-world experiments are implemented to prove our proposed signal identification method. Verification results show that a high right identification probability can be obtained with short observation time and low false alarm probability.

2 Preliminaries of LTE and GSM Signal Identification

2.1 Second-order Cyclostationarity

Signal identification is a binary hypothesis-testing problem [8]:

$$\begin{aligned} \mathrm{H}_0: \quad & \boldsymbol{y}(t) = \boldsymbol{n}(t) \\ \mathrm{H}_1: \boldsymbol{y}(t) &= \boldsymbol{x}(t) + \boldsymbol{n}(t). \end{aligned} \tag{1}$$

Under the hypothesis H_0, the received signal only contains Gaussian noise $\boldsymbol{n}(t) \sim \mathcal{N}\left(0, \sigma_{\mathrm{n}}^2\right)$, where $\mathcal{N}\left(0, \sigma_{\mathrm{n}}^2\right)$ is the Gaussian distribution with mean 0 and variance σ_{n}^2. Under the hypothesis H_1, the received signal is LTE or GSM signal $\boldsymbol{x}(t)$ plus the additive Gaussian noise $\boldsymbol{n}(t)$.

Given the second-order cyclostationarity of the random process $x(t)$, the autocorrelation function $R(t,\tau)$ can be expressed by the Fourier series as

$$R(t,\tau) = \sum_{\alpha} c(\alpha,\tau) e^{j2\pi\alpha t}, \tag{2}$$

where $\{\alpha\}$ consists of the integer multiples of the cyclic frequency α_0. If T_0 is a cycle of $R(t,\tau)$, then $\alpha_0 = \frac{1}{T_0}$. The CAF can be expressed as

$$c(\alpha,\tau) = \frac{1}{T_0} \int_{t=0}^{T_0} R(t,\tau) e^{-j2\pi\alpha t} \mathrm{d}t. \tag{3}$$

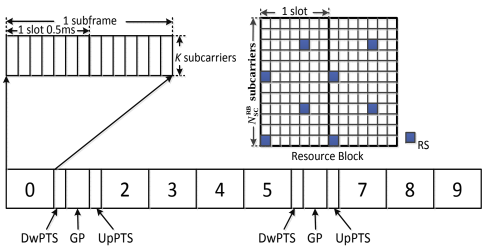


Fig. 1. The frame structure of TD-LTE.

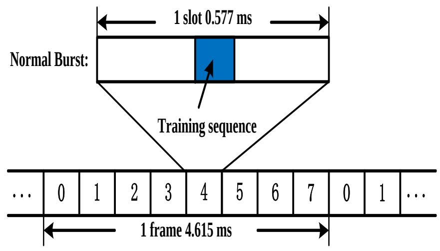


Fig. 2. The frame structure of GSM.

The sampling sequence of the signal $x(t)$ is denoted as $x(n)$. If the observation time is T_{total} and the sampling period is T_s, the length of $x(n)$ is $N = \frac{T_{total}}{T_s}$. $F_s = \frac{1}{T_s}$ is the sampling frequency. The unbiased estimation of $c(\alpha,\tau)$ is

$$\hat{c}(\alpha,\tau) = \frac{1}{N} \sum_{n=0}^{N-1} x(n) x^* \left(n + \frac{\tau}{T_s}\right) e^{-j2\pi\alpha n T_s}, \tag{4}$$

where τ is the integer multiply of T_s. The second-order samples are $r^\tau(n) = x(n) x^* \left(n + \frac{\tau}{T_s}\right)$. Therefore, the vector consisted of samples of $\hat{c}(\alpha,\tau)$ in the cyclic frequency domain, which is defined as $\boldsymbol{c}^\tau = \left[\hat{c}(0,\tau), \hat{c}\left(\frac{F_s}{N},\tau\right), \cdots, \hat{c}\left(\frac{(N-1)F_s}{N},\tau\right)\right]$ is

$$\boldsymbol{c}^\tau = \frac{1}{N} \boldsymbol{D}_N \boldsymbol{r}^\tau, \tag{5}$$

where $\boldsymbol{D}_N$ is an N dimensional DFT matrix and $\boldsymbol{r}^\tau = \left[r^\tau(0), r^\tau(1), \cdots, r^\tau(N-1)\right]^{\mathrm{T}}$ is the vector form of $r^\tau(n)$.

2.2 The Frame Structures of TD-LTE and GSM

The second-order cyclostationarity based signal identification is closely depends on the frame structure of the signal. The frame structure of TD-LTE is shown

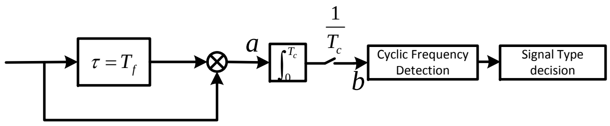


Fig. 3. The proposed detection diagram.

in Fig. 1 [10]. A TD-LTE frame contains 20 time slots, each with 6 or 7 OFDM symbols. In each time slot, $N_{\mathrm{SC}}^{\mathrm{RB}}$ subcarriers constitute a resource block (RB). The reference signals (RSs) used for cell identification are embedded in the RBs as shown in Fig. 1. Since reference signals are repeated in each time slot, LTE signal exhibits second-order cyclostationarity.

The frame structure of GSM signal is depicted in Fig. 2 [11]. Each GSM frame contains 7 time slots. A time slot might be the normal bursts for data transmission and the control bursts for synchronization, access, etc. In each normal burst, the training sequence used for channel estimation occupy 26 bits. The second-order cyclostationarity of the GSM signal comes from the periodicity of the training sequences.

For LTE signals, the period of reference signals is $T_{0,\mathrm{LTE}} = 0.5ms$. So the cyclic frequency is $\alpha_{0,\mathrm{LTE}} = \frac{1}{T_{0,\mathrm{LTE}}} = 2\mathrm{kHz}$. And for GSM signals, the period of training sequences is $T_{0,\mathrm{GSM}} = 0.577\mathrm{ms}$. So the cyclic frequency is $\alpha_{0,\mathrm{GSM}} = \frac{1}{T_{0,\mathrm{GSM}}} = 1.733\mathrm{kHz}$. These features are used to identify signals.

3 The Compressed Sensing Based Identification Method for LTE and GSM Signals

In this section, we present an enhanced method to identify LTE and GSM signals as depicted in Fig. 3. First, a noval structure is introduced to achieve sub-Nyquist sampling rate. Then, a low-complexity algorithm based on compressed sensing is used to estimate the cyclic frequencies. Finally, we elaborate the decision rule. The detection diagram is shown in Fig. 3.

3.1 Signal Sampling

The band of the target signal is usually broad, but the cyclic frequencies may not be very high. As our aim is to identify the signal, the sampling rate can be much lower than the Nyquist rate.

In our proposed structure, the samples are obtained from the second-order signals, which is obtained by multiplying the original signal with the delayed signal. The delay is $\tau = T_f$, where T_f is the frame length of the target signal. In this way, the second-order cyclostationarity of the target signal is more significant. The signal at a in Fig. 3 can be represented as

$$r(t) = y(t)\, y(t + T_f)\,. \tag{6}$$

In order to sample the second-order signal with a low rate, the mean of the second-order signal is calculated every T_c period before sampling. According to

Algorithm 1 Cyclic frequencies detection via OMP

Input: Second-order signal samples $\boldsymbol{r}_2$; dictionary matrix $\boldsymbol{Q}$

Initialization: $\boldsymbol{res} = \boldsymbol{r}_2$; $\boldsymbol{I} = []$

1: **for** $k = 1 : K$ **do**
2: $i = \text{argmax}\left(\boldsymbol{res}^{\mathrm{H}}\boldsymbol{Q}\right)$ // Find the most relevant item form the dictionary.
3: $\boldsymbol{I} = [\boldsymbol{I}, i]$, $\Psi = \boldsymbol{Q}\left(:, \boldsymbol{I}\right)$
4: $\hat{\alpha}_k = (i-1)\,\Delta\alpha$ // Calculate the cyclic frequency corresponding to the selected index.
5: $\boldsymbol{res} = \hat{\boldsymbol{c}} - \Psi\left(\Psi^{-1}\Psi\right)\Psi^{-1}\hat{\boldsymbol{c}}$ // Remove the influence of the estimated cyclic frequencies.
6: **end for**

Output: Estimated cyclic frequencies $\hat{\alpha}_k \; (k = 1, 2, \cdots, K)$.

the Nyquist sampling theory, the maximum cyclic frequency should be smaller than $\frac{1}{2T_c}$. The signal at b is denoted as

$$r_1(p) = \frac{1}{T_c}\int_{t=(p-1)T_c}^{pT_c} r(t)\,\mathrm{d}t. \tag{7}$$

The vector form of $r_1(p)$ is $\boldsymbol{r}_1 = [r_1(1), r_1(2), \cdots, r_1(N_1)]$, where $N_1 = \frac{T_1}{T_c}$. T_1 is the observation time. The CAF vector can be denoted as $\boldsymbol{c} = \boldsymbol{D}_{N_1}\boldsymbol{r}_1$, whose resolution is $\Delta\alpha = \frac{1}{T_1} = \frac{1}{T_c N_1}$. The observation time should be long enough to obtain a high CAF resolution.

3.2 The Identification Method

As mentioned above, signal identification requires a long observation time, which is generally many frame periods. In fact, a short observation time is e-nough because CAF is sparse in cyclic domain. This means that the recovery of CAF is a compressed sensing problem. We define a short-time observation $\boldsymbol{r}_2$ that is the first N_2 elements of $\boldsymbol{r}_1$. Namely, $\boldsymbol{r}_2$ contains the samples within the observation time $T_2\,(T_2 \ll T_1)$. If we use the knowledge of $\boldsymbol{r}_2$ to recover CAF $\boldsymbol{c}$, the compression ratio is $\beta = \frac{N_2}{N_1} = \frac{T_2}{T_1}$. Thus, the recovery problem is

$$\min_{\boldsymbol{c}} \|\boldsymbol{c}\|_0, \text{ subject to } \boldsymbol{r}_2 = \boldsymbol{Q}\boldsymbol{c} \tag{8}$$

where $\|\cdot\|_0$ is the l_0 norm to count the number of non-zero entries, and $\boldsymbol{Q} \in \mathbb{C}^{(N_2 \times N_1)}$ is the first N_2 columns of N_1 order IDFT matrix.

Orthogonal matching pursuit (OMP) is used so solve the recovery problem, which is given in Algorithm 1. K estimated cyclic frequencies are worked out in K loops. K should be larger than the number of the cyclic frequencies. But larger K will lead to larger false alarm probability. In each loop, the index of the column in $\boldsymbol{Q}$ which has the largest correlation with the residue is selected. The estimated cyclic frequency is calculated according to the index and the expected cyclic frequency resolution $\Delta\alpha = \frac{1}{T_1}$. Then a new residue is obtained by eliminating the contributions of the estimated cyclic frequencies.

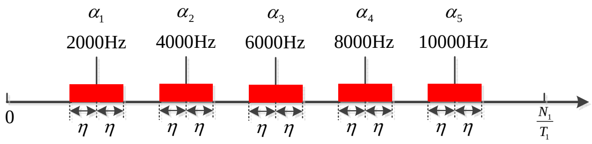


Fig. 4. An example of neighborhoods of cyclic frequencies. $\alpha_0 = 2000\text{Hz}, Z = 5$.

The identification needs to decide whether the target signal has the cyclic frequencies of LTE or GSM $\{\alpha_z | \alpha_z = z\alpha_0, (z = 1, 2, \cdots, Z)\}$, where α_0 is $\alpha_{0,\text{LTE}}$ or $\alpha_{0,\text{GSM}}$, and Z is the number of cyclic frequencies to be detected. The decision rule is that if an estimated cyclic frequency $\hat{\alpha}_k\,(k = 1, 2, \cdots, K)$ satisfies $|\hat{\alpha}_k - \alpha_z| < \eta$, where η is a predefined threshold, the target signal has the cyclic frequency α_z.

The signal type is decided using a voting rule. If the target signal has an cyclic frequency a_z, we have $\varDelta_z = 1$. If $\sum_{z=1}^{Z} \varDelta_z \geq V$, the occasion is decided as H_1. Else, the occasion is decided as H_0.

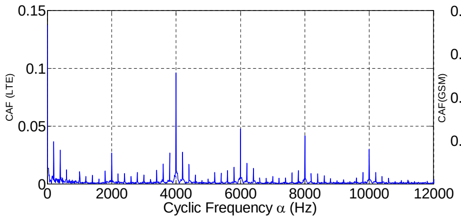
The false alarm probability is determined by the two threshold η and V. For the noise case H_0, the possible positions of the peaks are uniformly distributed in the cyclic domain with the employment of OMP. Considering the decision rule, the false alarm probability is the probability that no less than V estimated cyclic frequencies locate in the neighborhoods $U(\alpha_z, \eta), (z = 1, 2, \cdots, Z)$, which are the red ranges in Fig.4. From this figure, we can easily find that the probability that one cyclic frequency locates in $U(\alpha_z, \eta)$ is $P_e = \frac{2Z\eta T_1}{N_1}$. So the false alarm probability is

$$P_f = P(\text{H}_1 | \text{H}_0) = 1 - \sum_{k=0}^{V-1} C_K^k P_e^k (1 - P_e)^{(K-k)}. \tag{9}$$

4 Performance Evaluation by Measured Data

The experiment conditions are given first. The on-the-air signals were measured by the spectrum analyzer RSA306B from tektronix company. Real-world cellular signals are down converted from RF to baseband by RSA306B. And IQ data can then be processed with MATLAB software. We measured TD-LTE signal of Band 33 with the frequency range 1885-1905 MHz and the downlink GSM signal with the frequency range 935-954 MHz. The CAF of the measured signal with length $T_1 = 100\text{ms}$ is calculated and shown in Fig. 5 and Fig. 6. Significant peaks exist at some integer multiples of the two cyclic frequencies $\alpha_{0,\text{LTE}} = 2\text{kHz}$ and $\alpha_{0,\text{GSM}} = 1.733\text{kHz}$, respectively.

Then, the measured data is used to simulate the proposed sampling structure and the identification method. Since the cyclic frequencies ($\alpha_z \leq 10\text{kHz}$) is much smaller than the signal bandwidth (20MHz), the sampling rate can be lower than the Nyquist rate with the proposed sampling structure if the only purpose is identification. In our simulations, the sampling rate is set as $F_s = \frac{1}{T_c} = 56\text{kHz}$, and the compression ratio is set as $\beta = 0.1$, which means the observation time is $T_2 = 10\text{ms}$. The number of iterations of OMP is set as $K = 20$ in order to recover



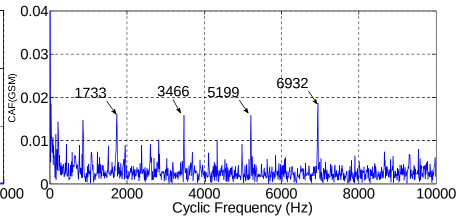
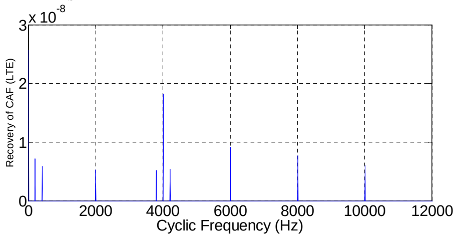


Fig. 5. CAF of TD-LTE with the observation time $T_1 = 100ms$, the central frequency is 1895MHz and the sampling rate $F_{\rm s} = 56$MHz.

Fig. 6. CAF of GSM with the observation time $T_1 = 100ms$, the central frequency is 945MHz and the sampling rate $F_{\rm s} = 28$MHz.



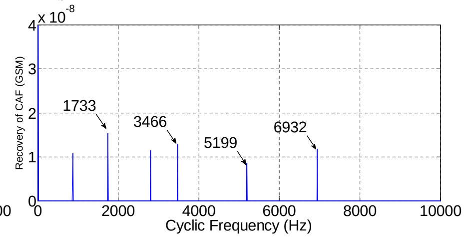


Fig. 7. The recovery of CAF of TD-LTE with the compression ratio $\beta = 0.1$.

Fig. 8. The recovery of CAF of GSM with the compression ratio $\beta = 0.1$.

all peaks. The recovery of CAF is shown in Fig. 7 and Fig. 8. The positions of the peaks are precisely estimated by OMP algorithm.

In the decision step, the voting threshold is $V = 2$. The false alarm probability is decided by the threshold η. In our simulations, η is set as 10Hz, 20Hz and 30Hz, corresponding to different false alarm probabilities. The number of cyclic frequencies to be detected is set as $Z = 5$ for LTE identification. And for GSM identification, $Z = 4$. The probability of right identification $P_{\rm d} = P\left(H_1|H_1\right)$ versus signal to noise ratio (SNR) is illustrated in Fig.9. We adjusted the SNR in our simulations by adding emulational noise to the measured data. The compression ratio is 0.1 in this simulation. As shown in this figure, a high performance is achieved with small false alarm probability.

The influence of the compression ratio on the probability of correct identification is illustrated in Fig.10. The SNR is set as -2dB, -4dB and -6dB. The threshold η is set as 10Hz. Namely the false alarm probability is 5.9×10^{-4} for TD-LTE and 3.8×10^{-4} for GSM. From this figure, we get the conclusion that a high performance can be achieved with low compression ratio (short observation time) when the SNR is not very small.

5 Conclusion

In this paper, we focused on the low-complexity identification of the practical LTE and GSM signals. We measured TD-LTE and downlink GSM signals by a spectrum analyzer. Then a low-rate sampling structure and an OMP-based method were employed to identify the signals. The performance of the compressed sensing based method was evaluated by measured data. Numerical re-

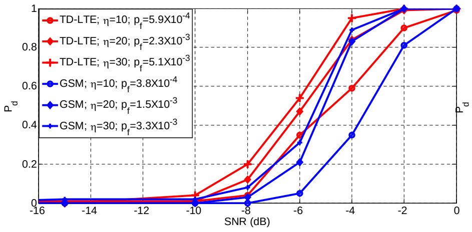


Fig. 9. The probability of correct detection versus SNR with different false alarm probabilities. The compression ratio is 0.1.

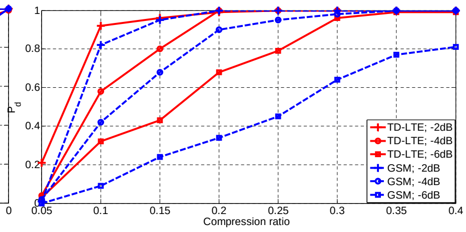


Fig. 10. The probability of correct detection versus compression ratio with different SNR. False alarm probability is 5.9×10^{-4} for TD-LTE and 3.8×10^{-4} for GSM.

sults show that a high right identification probability is obtained with short observation time and low false alarm probability. For future work, it would be interesting to identify signals in the condition that diverse signals possibly exist.

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