An Energy Approximation Model Based on Restricted Isometry Property in Compressive Spectrum Sensing for Cognitive Radio

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Abstract —Compressive Sensing (CS) has proved to be an effective technique in terms of spectrum sensing of Cognitive Radio (CR). However the signal reconstruction is costly and unnecessary. Through analysis of Restricted Isometry Property (RIP) of CS, it is feasible to detect the primary user directly through the compressed signal. In this paper, a novel Energy Approximation model based on Compressive Spectrum Sensing (EA-CSS) in cognitive radios is proposed. In contrast with the traditional compressive spectrum sensing scheme, this method does not need to reconstruct the original signal and has lower complexity algorithms at the same time. In the modeling, the observed signal energy and the original signal energy is nearly equal. The cooperative sensing based on this model is also improved and shows more robust to the noise compare with the common cooperative sensing scheme. Simulation results show that the proposed techniques have a reliable detection performance with small number of samples.

Index Terms—Compressed Sensing (CS), Cognitive Radio (CR), Energy Approximation (EA), Restricted Isometry Property (RIP), cooperative sensing

I. Introduction

In recent decades, rapid growth in wireless communication service makes the limited spectrum resources become increasingly scarce. Cognitive radio [1] can solve this problem by dynamic spectrum access technology. Spectrum sensing is one of the key technology of cognitive radios and the quick and accurate perception of broadband spectrum hole is the main challenge.

In order to improve the efficiency of spectrum sensing, it's necessary to apply the wideband spectrum sensing. However the main challenge in the wideband spectrum sensing applications is the fast sampling rate which is difficult to realize by modern sampling system. Then, Compressed Sensing (CS) is proposed [2], which makes it possible to reconstruct the sparse or compressible signals from far fewer samples than Nyquist samples [3], [4] Therefore, CS can be used for wideband spectrum sensing because of the sparsity of spectrum data [5], [6].

Manuscript received March 5, 2015; revised July 17, 2015.

This work was supported by the Ph.D. Programs Foundation of Ministry of Education of China under Grant No. 2013102SBJ0265.

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doi:10.12720/jcm.10.7.490-496

Thus, in recent years, a variety of wideband compressed sensing algorithm emerged. Reference [7]-[10] proposed that we can reduce the sampling rate through CS and detect the spectrum of reconstructed signals. Although this algorithm can obtain an excellent detection performance, the disadvantage of this approach is that it requires to reconstruct the original signal before the spectrum sensing. However, compressed sensing reconstruction algorithm has certain complexity and instability and undoubtedly increase the complexity of cognitive radio system. Reference [11] proposed the spectrum sensing without reconstructing the signals, but the detection performance is not very good when the SNR is low. Then many effective solutions [12]-[14] have been given to this problem. Reference [12] proposed a high-order statistics based on compressive measurements for the wideband spectrum sensing scheme; Reference [13] proposed a novel compressed spectrum energy detection scheme based on wavelet transform; Reference [14] proposed a Compressive Signal Processing (CSP) model to detect spectrum holes without to analyze the entire signal.

In real CR system, a single cognitive radio may fail to accurately sense and detect a hidden node of a primary user because of shadowing or low signal to noise power ratio (SNR) [15]. The cooperative sensing can solve the problem, so the further research with the cooperative compressed sensing is quite necessary. Reference [16] proposed a centralized collaborative compressed spectrum sensing scheme, which choose an compressive sampling matrix linearly related to the original signals to apply algebraic detector. Reference [17] proposed a parallel spectrum sensing model which gets the final decision from the results of each branch after using CS and wavelet to process the input in all branches.

In order to reduce the single compressive spectrum sensing scheme's complexity, in this paper, we present a new compressive spectrum sensing based on energy approximation model. In the proposed scheme the spectrum sensing can be completed directly from the compressed signals without signal reconstruction. Furthermore, in order to strengthen the stability and reliability of the system in real CR system, centralized cooperative spectrum sensing will be added to the design.

The rest of this paper is organized as follows. Section II introduces the compressive sensing and cooperative spectrum sensing theory. Section III proposes a new compressive spectrum sensing based on energy approximation model. Finally, simulation results and discussions are presented in Section IV and the conclusion is drawn in Section V.

II. Compressive Sensing and Cognitive Radio

A. Compressive Sensing

IF there is a length-N discrete signal x whose non-zero coefficients $K << N$, x is called K-sparse signal. Suppose that x can be represented in accordance with a basis of $N\times1$ vectors $\{\Psi_i\}_{i=1}^{N}$ and the basis is orthogonal [18],[19]. Accordingly, x can be expressed as:

$$x=\Psi\Theta \Leftrightarrow \Theta=\Psi^T x \tag{1}$$

where x is compressible if Θ is sparse. To observe M linear measurements y of x we can get a $M\times N$ $(M<<N)$ measurement matrix Φ that is incoherent with Ψ

$$y=\Phi\Theta=\Phi\Psi^T x=A^{CS}x \tag{2}$$

The signal reconstruction phase is focused on the recovery of Θ from the measurement vector y [20], [21]. Ψ is a known matrix, so the recovery of Θ means the reconstruction of original signal x. Under the condition of $M<<N$, the reconstruction is equal to solving the l_0-norm optimization problem of equation (2) .

$$\min\|\Theta\|_0 \quad s.t.\ \ \Phi\Theta=y \tag{3}$$

However solving equation (3) is the NP-hard problem. In order to reduce complexity, l_1-norm optimization problem is used as alternative [22], [23].

$$\min\|\Theta\|_1 \quad s.t.\ \ \Phi\Theta=y \tag{4}$$

B. Cooperative Spectrum Sensing

The centralized cooperative spectrum sensing model [24], [25] is illustrated in Fig. 1. It mainly consists of the primary base station (PBS), the Cognitive User (CU) and the Fusion Center (FC).

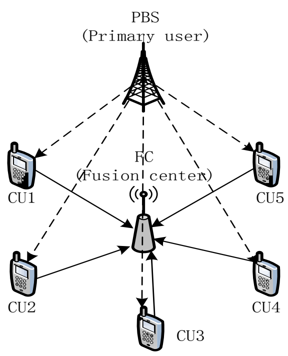

Fig. 1. Centralized cooperative spectrum sensing model

Firstly, each cognitive user detects the signal transmitted by the primary base station, and then sends the detection results to the fusion center which will make a final decision. As is known to all, the Energy Detection (ED) [26] is simple and easy to implement, so it is regular used for cooperative spectrum sensing in the local detection. The energy detection model is depicted in Fig. 2.

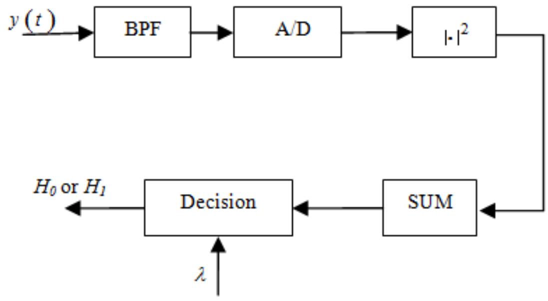

Fig. 2. Energy detection model

The local spectrum sensing problem can be formulated as the following two hypotheses

$$y_k=\begin{cases}x+n & H_1\\ n & H_0\end{cases} \tag{5}$$

where y_k is the signal received by cognitive user and x is the primary user's transmitted signal and n is the Additive White Gaussian Noise (AWGN). H_0 is the null hypothesis stating that the received signal y corresponds to the noise n and therefore there is no primary user in the sensed spectrum band; instead, H_1 means that some primary user is present.

Then the decision statistic T of the energy detection model can be written as

$$T=\sum_{k=0}^{N}|y_k|^2 \tag{6}$$

where N denotes the number of samples collected during the sensing period and λ is the final threshold to distinguish between the two hypotheses in (5). If $T>\lambda$, PU is present and H_1 is decided; if $T<\lambda$, PU is not present and H_0 is decided. Suppose that only AWGN is considered, the detection probability pd and false alarm probability pfa can be expressed as

$$pd=P\{T>\lambda\,|\,H_1\}=Q_m(\sqrt{2\gamma},\sqrt{\lambda}) \tag{7}$$

$$pfa=P\{T>\lambda\,|\,H_0\}=\frac{\Gamma(m,\ \lambda/2)}{\Gamma(m)} \tag{8}$$

where γ is the signal to noise power ratio, $\Gamma(\cdot,\cdot)$ is the incomplete gamma function and $Q(\cdot)$ is the Gaussian tail probability Q-function.

Suppose that there are M CUs in the centralized cooperative spectrum sensing model, the detection probability of CU_i is $P_d^i\,(\mathrm{i}=1,2,\ldots M)$ and the false alarm probability is $P_f^i\,(\mathrm{i}=1,2,\ldots M)$. The final decision is made according to the "OR" and "AND" fusion algorithm.

(1) "OR" fusion rule

$$P_d = 1 - \prod_{i=1}^{M}(1 - P_d^i) \tag{9}$$

$$P_f = 1 - \prod_{i=1}^{M}(1 - P_f^i) \tag{10}$$

(2) "AND" fusion rule

$$P_d = \prod_{i=1}^{M} P_d^i \tag{11}$$

$$P_f = \prod_{i=1}^{M} P_f^i \tag{12}$$

III. ENERGY APPROXIMATION MODEL

A. Energy Approximation at an Individual Radio

For the aim of spectrum holes detection, The problem of local compressive spectrum sensing can be formulated concisely as the following two hypotheses in accordance with (2) and (5)

$$y_k = \begin{cases} \Phi(x+n) & H_1 \\ \Phi n & H_0 \end{cases} \tag{13}$$

To state the new energy approximation model, we first review the important concept of Restricted Isometry Property (RIP) in CS.

Definition 1: For each integer $k = 1,2,3,\ldots$, define isometry constant δ of a matrix Φ as the smallest number such that

$$(1-\delta)\|x\|_2^2 \le \|\Phi x\|_2^2 \le (1+\delta)\|x\|_2^2 \tag{14}$$

We say that matrix Φ obeys the RIP of order K if $0<\delta<1$.

Reference [27] proposed that for any $x \in R^N$, the random variable $\|\Phi x\|_2^2$ is highly concentrated about $\|x\|_2^2$; that is, there exits a constant $C_1 > 0$ depending only on δ such that

$$\Pr\left(\left|\|\Phi x\|_2^2 - \|x\|_2^2\right| \ge \delta\|x\|_2^2\right) \le 2e^{-C_1\delta^2 M}, 0<\delta<1 \tag{15}$$

where the probability is taken over all $M \times N$ matrices Φ.

Lemma 1: Let $x \in R^N$ be a sparse signal and y be a measurement vector. If there is a $M \times N$ random matrix Φ whose entries satisfy independent and identically distributed $\Phi_{i,j} \sim \left(0, \frac{1}{M}\right)$ then

$$\Pr\left(0.693 < \frac{\|y\|_2^2}{\|x\|_2^2} < 1.307\right) \ge 1 - 2e^{-CM},\ C>0 \tag{16}$$

Proof: Inequality (14) is equivalent to

$$\Pr\left(\left|\|\Phi x\|_2^2 - \|x\|_2^2\right| \le \delta\|x\|_2^2\right) \ge 1 - 2e^{-C_1\delta^2 M}, 0<\delta<1 \tag{17}$$

Upon combining (2), one obtains the following inequality:

$$\Pr\left(\left|\|y\|_2^2 - \|x\|_2^2\right| \le \delta\|x\|_2^2\right) \ge 1 - 2e^{-C_1\delta^2 M}, 0<\delta<1 \tag{18}$$

Reference [28] proposed new bounds for δ. It shows that if

$$0<\delta<0.307 \tag{19}$$

the sparse signal can be correctly recovered in the noise-free case and estimated stably in the noisy case via $l_1 - norm$ optimization .

Upon combining (18), one obtains the following inequality:

$$\Pr\left(\left|\|y\|_2^2 - \|x\|_2^2\right| < 0.307\|x\|_2^2\right) > 1 - e^{-CM}, C>0 \tag{20}$$

The inequality model

$$\left|\|y\|_2^2 - \|x\|_2^2\right| < 0.307\|x\|_2^2 \tag{21}$$

Can be equivalent to

$$-0.307\|x\|_2^2 < \|y\|_2^2 - \|x\|_2^2 < 0.307\|x\|_2^2. \tag{22}$$

Then,

$$0.693\|x\|_2^2 < \|y\|_2^2 < 1.307\|x\|_2^2 \tag{23}$$

Therefore,

$$0.693 < \frac{\|y\|_2^2}{\|x\|_2^2} < 1.307 \tag{24}$$

which proves Lemma 1.

From Lemma 1, we find that the ratio of the compressed signal energy $\|y\|_2^2$ is close to the original signal energy $\|x\|_2^2$. That is, the observed signal energy and the original signal energy is nearly equal.

In order to make Lemma 1 more explicit, Fig. 3 depicts the $\|y\|_2^2 / \|x\|_2^2$ for Gaussian random matrix of $M = 200$, $N = 1024$, under 10000 times simulation. We note that the $\|y\|_2^2 / \|x\|_2^2$ of Gaussian random matrix satisfied the range of $(0.63, 1.307)$ to a great extent. Even in most cases, the range is $(0.9, 1.1)$.

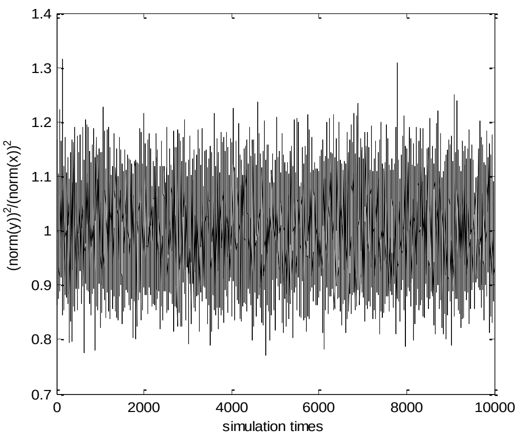

Fig. 3. Compressive signal energy to the original signal energy ratio in the absence of noise.

However in real CR system, we have to consider the case of low SNR. When there is noise n, we will get the compressed signal $y=\Phi x=\Phi\left(x_0+n\right)$. Fig. 4 represents the $\|y\|_2^2/\|x\|_2^2$ for Gaussian random matrix of $M=200$, $N=1024$ when $\mathrm{SNR}=-10\ \mathrm{dB}$. We note that the $\|y\|_2^2/\|x\|_2^2$ also satisfied the range of (0.63,1.307) to a great extent. It's a very exciting result.

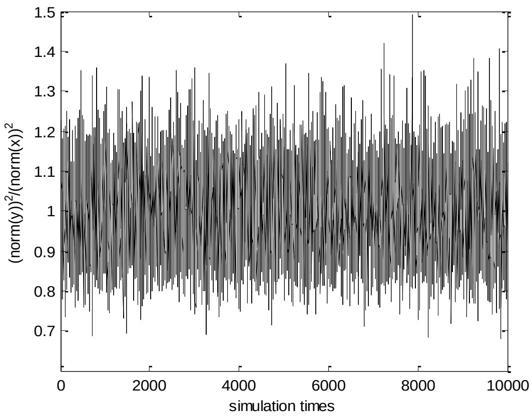

Fig. 4. Compressive signal energy to the original signal energy ratio in the noise.

Now we define $d=\left|1-\|y\|_2^2/\|x\|_2^2\right|$ that represents the difference between the compressive signal energy to the original signal energy. Fig. 5 depicts the average value of d when the SNR of received signal varies in certain range. As expected, the compressive signal energy and the original signal energy is almost equal.

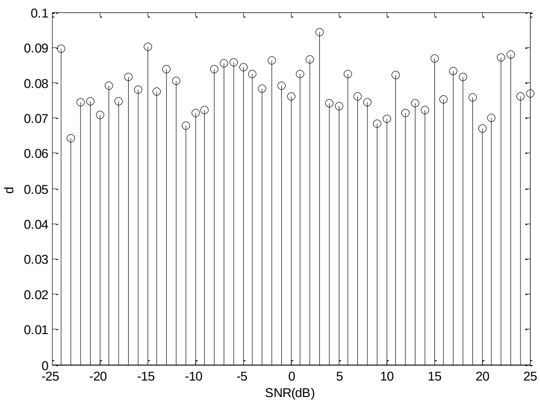

Fig. 5. Compressive signal energy to the original signal energy ratio under various SNR.

Because the task of spectrum sensing is to merely perceive whether the primary user exists, we do not need to analyze the complete signal. And the principle of energy detection is to compute the absolute value of the square in the time domain or frequency domain. Then we can determine the presence or absence of the primary user according to a suitable threshold.

Now, the observed signal energy is practically equal to the original signal enery under noiseless or even in the environment of the low SNR. Therefore, we don't have to care about the difference of the observed signal and the original signal to acquire lower samples. Then, we can replace the input signal x with the compressed signal y in the energy detection directly which is our energy approximation (EA) model.

B. Energy Approximation at the Fusion Center

In order to overcome the unreliable individual observations of each CR user, in our EA-CSS scheme, the centralized cooperative spectrum sensing can be added to the design. We proposed a cooperative sensing model, which structure is depicted as Fig. 6 based reference [17]. Where Φ_k is the measurement matrix and different Φ_k functions in different branches. And different Φ_k stands for different compressed sampling. In this way, the sensing error of some branches that the energy of sampling results y and the original signal x are deviated largely can be avoided effectively.

By Lemma 1, this system can work correctly with the probability of

$$1-2^k e^{-C\sum_{i=1}^{k} M_i} \approx 1 \tag{25}$$

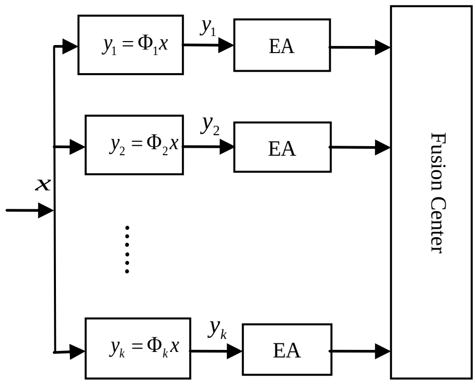

Fig. 6. Centralized cooperative spectrum sensing structure based on CS

IV. COMPUTATIONAL EXAMPLES AND ANALYSIS

In this section, simulation environment is Matlab R2009a, Gaussian random matrix and sparse signals are used.

We first explore the detection performance of the compressive spectrum sensing based on Energy Approximation model (EA-CSS) vs. the Energy Detector (ED). The compressive ratio $M/N=0.5$, false alarm probability $pfa=0.1$. Fig. 7 illustrates the detection probability vs. SNR. When $SNR>\text{-}5dB$, the detection probability of this method can achieve 1. It means that in high SNR, EA-CSS can perform almost as well as the traditional detector with lower sampling rate. Then the probability of detection is less than the energy detection when $\text{-}13dB<SNR<\text{-}4dB$. The reason is that the energy of the compressed signal and the original signal are not exactly equal and it is just an estimate. However, the expense of the detection probability in exchange for a portion of the lower sampling rate is acceptable. When

$SNR < -25dB$, both probabilities of detection are very low, the probability of detection of this method is higher than the energy detection. This is because when SNR is very low, A portion of the energy of the noise can be reduced by the energy difference of compressed signal and original signal.

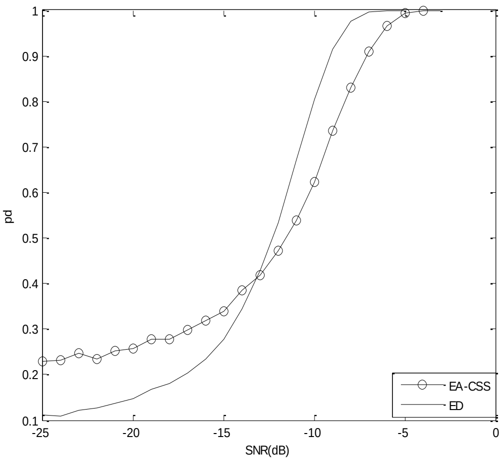

Fig. 7. The detection performance of EA-CSS and ED

Then, we investigate the detection probability vs. compressive ratio of EA-CSS. Fig. 8 depicts the P_d for the different compressive ratio (M/N) and SNR in $pfa = 0.1$. When $SNR = 0dB$, the detection probability can achieve 1 no matter what the compression ratio is. It means that we can achieve very high detection rates with a low false alarm and sampling rate. We note that the detection probability grows as we increase SNR under the same compression ratio. And under the same SNR, the detection probability grows as we increase the compression ratio. However lower compression ratio is our goal. So we should find a tradeoff between the compression ratio and the probability of detection.

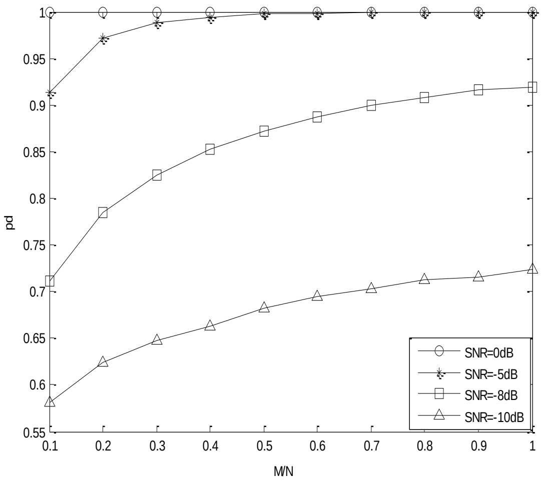

Fig. 8. Detection probability Vs Measurements

Next , we investigate the detection probability vs. false alarm probability (pfa) of EA-CSS. Fig. 9 depicts the P_d for different pfa and compressive ratio (M/N) in $SNR = -5dB$. We note that under the same pfa the detection probability grows as we increase M/N, meaning that we can achieve a high P_d while keeping pfa very low. As M/N grows we see that it's a problem of the tradeoff between P_d and pfa.

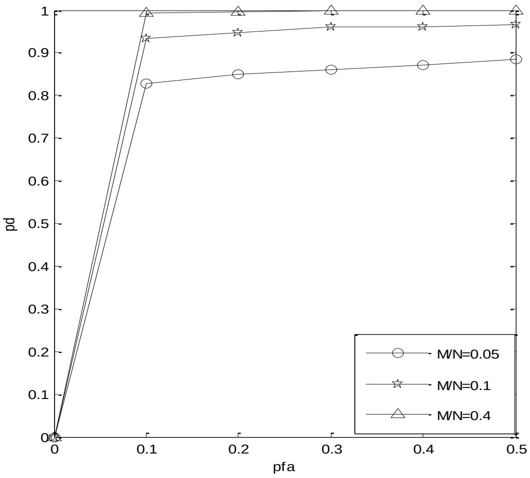

Fig. 9. Detection probability Vs Alarm probability

Finally, we investigate the detection performance of centralized cooperative spectrum sensing model based on the energy approximation. When the alarm probability is 0.1, the compressive ratio $M/N = 0.5$ and the number of cognitive users is 6, we compare the detection probability of OR and AND fusion policies and single-node sensing under various number probability of false alarm and the result is illustrated in Fig. 10. We realize that OR rule's detection probability is the highest among the three under the same SNR. It is because that OR rule only requires one CR user detects PU then the fusion center believes it exists. However AND is relatively strict, only if all of the CR users detects PU the fusion center believes it exists. So the curve of AND rule lies below the others.

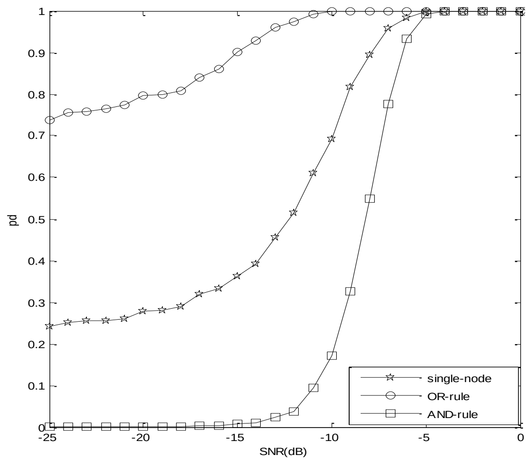

Fig. 10. Cooperative sensing Vs Single-node sensing

V. CONCLUSIONS

In this paper an energy approximation based on RIP in compressive spectrum sensing for cognitive radio is proposed. The proposed technique utilizes an energy approximation modeling that the observed signal energy and the original signal energy is nearly equal to implement spectrum detection without the signal reconstruction. The simulation results show that the detection performance is not inferior to energy detection and with a lower sampling rate. Furthermore, through the improved centralized cooperative spectrum sensing model based on the energy approximation, we get a more stable and reliable performance. Therefore, this model is feasible in cognitive radios.

ACKNOWLEDGMENT

The authors wish to thank current master students Gang Liu and Meng-Ya Nie. This work was supported in part by a grant from Ph.D. Programs Foundation of Ministry of Education of China (No. 2013102SBJ0265).

REFERENCES

[1] J. Wang, M. Ghosh, and K. Challapali, "Emerging cognitive radio applications: A survey," *IEEE Communications Society*, vol. 49, no. 3, pp. 74-81, March 2011.
[2] D. Donoho, "Compressed sensing," *IEEE Trans. Info. Theory*, vol. 52, no. 4, pp. 1289-1306, April 2006.
[3] E. J. Candès and M. B. Wakin, "An introduction to compressive sampling," *IEEE Signal Processing Magazine*, pp. 21-30, March 2008.
[4] E. J. Candès and T. Tao, "Near optimal signal recovery from random projections: Universal encoding strategies?" *IEEE Trans. Info. Theory*, vol. 52, no. 12, pp. 5406-5425, Dec. 2006.
[5] Z. Tian and G. B. Giannakis, "Compressed sensing for wideband cognitive radios acoustics," in *ICASSP*, 2007, pp. IV-1357-IV-1360.
[6] Z. Tian, E. Blasch, and W. Li, "Performance evaluation of distributed compressed wideband sensing for cognitive radio network," in *Information Fusion*, 2008, pp. 1-8.
[7] L. Zhou and H. Man, "Wide-band spectrum sensing using neighbor orthogonal matching pursuit," in *Proc. IEEE Sarnoff Symp.*, May. 2012, pp. 1-5.
[8] S. E. El-Khamy, M. B. Abdel-Male, and S. H. Kamel, "A new wideband spectrum sensing technique based on compressive sensing, wavelet edge detection and parallel processing," in *NRSC.*, 2013, pp. 202-210.
[9] H. J. Sun, A. A. Nallanathan, and C. X. Wang, "Wideband spectrum sensing for cognitive radio networks: A survey," in *Wireless Communications*, 2013, pp. 74-81.
[10] A. S. Shariful, L. Marcenaro, and C. S. Regazzoni, "Enhanced performance in wideband cognitive radios via compressive sensing," in *GlobalSIP.*, pp. 1290-1293, April 2013.
[11] M. A. Davenport, P. T. Boufounos, and M. B. Wakin , "Signal processing with compressive measurements, "*IEEE Journal of Selected Topics in Signal Processing*, vol. 4, no. 2, pp. 445-460, 2010.
[12] K. T. Cao and H. Q. Shao, "Compressive wideband spectrum sensing using high-order statistics for cognitive radio," in *GHTCE.*, 2013, pp. 187-190.
[13] X. Han, W. B. Xu, and K. A. Niu, "Novel Wavelet-based Energy Detection for Compressive Spectrum Sensing, " in *VTC Spring*, 2013, pp. 1-5.
[14] A. Appaiah, A. Perincherry, A. S. Keskar, and V. Krishna, "Spectrum sensing in cognitive radio based on compressive measurements," in *C2SPCA*, 2013, pp. 1-6.
[15] Z. Tian, "Compressed wideband sensing in cooperative cognitive radio networks," in *IEEE "GLOBECOM" 2008 Proceedings*, 2008, pp. 1-5.
[16] H. Moussavinik, W. Guibene, and A. Hayar, "Centralized collaborative compressed sensing of wideband spectrum for cognitive radios," in *ICUMT*, 2010, pp. 246–252.
[17] C. Xi, L. J. Zhao, and J. D. Li, "A modified spectrum sensing method for wideband cognitive radio based on compressive sensing, " in *ChinaCOM*, 2009, pp. 1-5.
[18] R G. Baraniuk, "Compressive sensing," *IEEE Trans. Signal Process*, vol. 24, no. 4, pp. 118-121, 2007.
[19] E. J. Candès and J. Romberg, "Sparsity and incoherence in compressive sampling," *Inverse Problems*, vol. 23, no. 3, pp. 969-985, 2007.
[20] E. J. Candès, J. Romberg, and T. Tao, "Robust uncertainty principles:Exact signal reconstruction from highly incomplete frequency information," *IEEE Trans. Inf. Theory*, vol. 52, no. 2, pp. 489–509, Feb. 2006.
[21] J. Tropp and A. Gilbert, "Signal recovery from random information via orthogonal matching pursuit," *IEEE Trans. Inf. Theory*, vol. 53, no. 12, pp. 4655–4666, Dec. 2007.
[22] E. Candès and J. Romberg, "*l*1-MAGIC: Recovery of sparse signals via convex programming," *Caltech*, October 2005.
[23] T. Tony Cai, G. W. Xu, and J. Zhang, "On recovery of sparse signals Via *l*1 minimization" *IEEE Trans. Info. Theory*, vol. 55, no. 7, pp. 3388-3397, Jul. 2009.
[24] F. A. Ian, F. L. Brandon, and R. Balarkrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Physical Communication*, vol. 4, no. 1, pp. 40-62, March 2011.
[25] S. Mishra, A. Sahai, and R. Brodersen, "Cooperative sensing among cognitive radios," in *Proc. IEEE ICC*, 2006, vol. 4, pp. 1658–1663.
[26] K. Kim, Y. Xin, and S. Rangarajan, "Energy detection based spectrum sensing for cognitive radio: An experimental study," in *GLOBECOM*, 2010, pp. 1-5.
[27] R. Baraniuk, M. Davenport, R. DeVore, and M. Wakin, "A simple proof of the restricted isometry property for random matrices," *Const. Approx.*, vol. 28, no. 3, pp. 253–263, Dec. 2008.
[28] T. T. Cai, L. Wang, and G. W. Xu, "New bounds for restricted isometry constants," *IEEE Transactions on Information Theory*, vol. 56, no. 9, pp. 4388-4394, 2010.

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