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Research on Spectrum Sensing Technology for Integrated Space-Ground Network

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Abstract. The demand for wideband wireless spectrum is increasing rapidly due to a rapidly expanding market of satellite communications and multimedia wireless services while the usable spectrum is becoming scarce due to current spectrum segmentation and static frequency allocation policies. Cognitive Radio (CR) can be an efficient technique to increase the spectrum utilization efficiency of heterogeneous wireless networks. Compressive sensing (CS) can overcome the traditional restriction that sampling rate must satisfy the Nyquist sampling theory, and it is also an important technology available for the integrated space-ground network. Aiming at the problem that the measurement processes of orthogonal matching pursuit (OMP) are easy to be disturbed by noise and the sparse information may not be available for practical applications. To overcome these problems, we have extended the idea of OMP to illustrate another recovery scheme called stochastic gradient orthogonal matching pursuit (SGOMP). It's shown that the proposed algorithm shows robustness against noise. Moreover, with modified the early termination threshold (ETT), the complexity of the proposed algorithm can be reduced.

Keywords: cognitive satellite communication network, compressive sensing, early termination threshold, least mean square error, stochastic gradient pursuit

1 Introduction

With the continuous increasing of the global network and information requirements, ground communications network has been unable to meet the growing demand for information acquisition and transmission. Vehicle applications, mobile devices and the Internet of Things are growing has gradually get the attention of the industry [1]. Although the ground network is developing rapidly, due to the limitation of the coverage, the construction and the maintenance cost, it can only provide communications services to economically developed and populous urban areas. For offshore platforms, deserts and bipolar areas where such inaccessible but in need of reliable communications, terrestrial communication networks are even more powerless. Due to its wide coverage, flexible network configuration and good broadcast performance, satellite communication can achieve long-span information transmission through effective spatial networking and provide a feasible way for seamless

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coverage of communication services in the world. Once the terrestrial network is blocked or damaged, satellite communication network can also serve as a backup force for the terrestrial network, which can transmit and receive data packets through the satellite network, greatly improving the reliability of the communication network. In addition, satellite communication networks can provide the necessary relay channels for human space exploration activities. Satellite communication networks also have better multicast and broadcast capabilities than other modes of communication. With the exponential growth of information resources, multicast and broadcast technology are powerful means to solve the problem of insufficient communication bandwidth resources. With the development of aerospace technology, communication technology and satellite load capacity, communication technology of satellite communication networks are expected to support the ever-increasing types of services, the ever-increasing communication speeds and the ever-growing user base.

The demand for wideband wireless spectrum is increasing rapidly due to the rapid development of multimedia wireless services and high-throughput satellite technology. Time division multiplexing is widely used in satellite communications at present, but there is less research on spectrum utilization. Cognitive Radio (CR) can be an efficient technique to increase the spectrum utilization efficiency of heterogeneous wireless networks. However, how to use this technology in a hybrid network of multiple terrestrial wireless networks and satellite networks to improve the utilization rate of such networks is a hot issue. Cognitive Radio technology allows the coexistence of primary and secondary users within the same spectrum without obstructing the normal operation of the primary licensed systems. Spectrum sensing is one of the core technology in CR, but the high sampling rate has hampered the development of traditional wideband spectrum sensing seriously. compressive sensing (CS) can overcome the traditional restriction that sampling rate must satisfy the Nyquist sampling theory, and it is also an important technology available for the integrated space-ground network.

Compressive sensing is a technology that can efficiently acquire a signal using relatively few measurements, it can find the unique representation of signals based on the sparsity or compressibility of signals in some domains. As the wideband spectrum is inherently sparse due to its low spectrum utilization, compressive sensing becomes a promising candidate to realize wideband spectrum sensing by using sub-Nyquist sampling rates. Tian and Giannakis first introduced compressive sensing theory to sense wideband spectrum in [2]. This technique used fewer samples closer to the information rate, rather than the inverse of the bandwidth, to perform wideband spectrum sensing. After recovery of the wideband spectrum, wavelet-based edge detection was used to detect spectral opportunities across wideband spectrum.

The compressive sensing has made a revolutionary breakthrough in the field of communication, which has attracted the attention of researchers, to improve the robustness against noise uncertainty, Tian et al. [3] studied a cyclic feature detection-based compressive sensing algorithm for wideband spectrum sensing. It can successfully extract second-order statistics of wideband signals from digital samples taken at sub-Nyquist rates. The 2D cyclic spectrum (spectral correlation function) of a wideband signal can be directly recovered from the compressive measurements. In addition, such an algorithm is also valid for reconstructing the power spectrum of a wideband signal, which is useful if the energy detection algorithm is used for detecting spectral opportunities.

For further reducing the data acquisition cost, Zeng et al. [4] proposed a distributed compressive sensing-based wideband sensing algorithm for cooperative multihop cognitive radio networks. By enforcing consensus among local spectral estimates, such a collaborative approach can benefit from spatial diversity to mitigate the effects of fading. In addition, a decentralized consensus optimization algorithm was proposed that aims to achieve high sensing performance at a reasonable computational cost. A mechanism based on information fusion is proposed in [5] for reducing the volume of data being transferred. The mechanism is a trade-off between uploading the results of in-network data processing and uploading all of the raw data. Based on users' requirements, proper data will be uploaded, and the accuracy of querying will be as good as, or better than, uploading all of the raw data.

The existing compressive sensing based spectrum sensing algorithms can be divided into the $l1$ norm algorithm and the greedy algorithm. The $l1$ norm algorithm, which includes basis pursuit algorithm BP [6] and its optimization algorithm called gradient projection for sparse reconstruction (GPSR) [7], which can convert a combinatorial optimization problem into a convex optimization problem. The $l1$ norm algorithm can provide a theoretical performance guarantee. However, they are noise sensitive and computationally complex. The greedy algorithm approximates the spectral index set of the target signal by iteratively approximating the spectral index set of the signal, which is more efficient for large-scale reconstruction problems. At present, typical greedy algorithms include the orthogonal matching pursuit which called OMP algorithm [8], the ROMP algorithm [9] and the SOMP algorithm. The complexity of these algorithms is far lower than the $l1$ norm algorithms. However, they require a large amount of measurement data for accurate recovery and their anti-noise ability is weak. CoSaMP shows robustness against noise. However, for practical applications, the sparse information may not be available. In view of the above problems, an enhanced algorithm called stochastic gradient orthogonal matching pursuit (SGOMP) algorithm which based on the OMP algorithm is proposed in this paper.

This paper is organized as follows: In Section 2, we present architecture of the integrated Space-Ground network and the detailed description of the OMP algorithm. The proposed SGOMP algorithm is discussed in Section 3. In Section 4, some simulation analysis process and results are given. Finally, the Section 5 concludes with a summary of the obtained results.

2 Preliminaries

2.1 Integrated Space-Ground Network Architecture

Cognitive satellite communication network is a satellite communication network system using cognitive radio technology, it also involves the use of cognitive satellite (unassigned communication satellite) to the terrestrial licensed band and satellite licensed band. Cognitive satellite communication technology allows unlicensed satellites to use the licensed satellite link or the licensed land link frequency band for uplink downstream communication without prejudice to the normal communication of authorized users. Therefore, more satellite users can be developed to further promote the development of satellite communications. Enriching relevant research in this field will play an important role in promoting the utilization of spectrum resources, improving the quality of satellite communications services and system capacity, and promoting the development of satellite communications.

A typical topology of integrated Space-Ground network is shown in Fig. 1. According to the location in the network, integrated Space-Ground network can be divided into two parts: access satellite network and backbone satellite transport network. The access satellite network is responsible for the connection between the space-based satellites, satellite and user terminals and between satellite and ground gateway, so as to fully realize the effective interconnection of the space information network with the ground core network and the ground terminal users so as to effectively use the space, the air, the sea and other multi-dimensional information to achieve the integrated and complex processing of integrated networks and the maximum effective use of. The backbone satellite transport network consists of a single-layer satellite constellation with the same orbital altitude or a multi-layer satellite constellation without orbital altitude, and completes the routing, exchange and transmission process of the communications service in the space network part through the inter-satellite link.

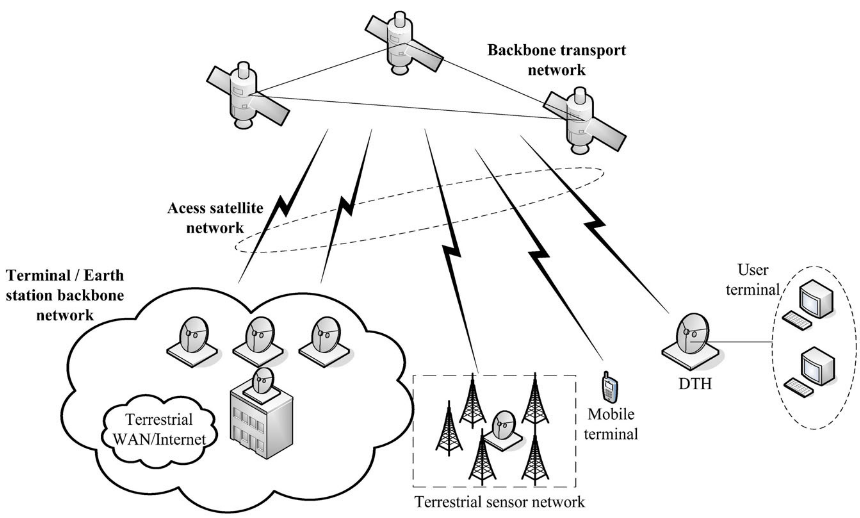

Fig. 1. Integrated Space-Ground network topology

2.2 OMP for Compressive Sensing Recovery

The compressive sensing can be modeled in matrix form as:

$$y = \Phi x + n \tag{1}$$

There are two basic problems in compressive sensing. The first one is to find a measurement matrix which can ensures every k-sparse signal has a unique measurement. The second problem in CS is to find a suitable algorithm that can exactly recover any sparse signal from its unique measurements.

In the problem of compressive sensing recovery using OMP, it is known a priori that the measured signal is k-sparse, which means has non-zero entries only at unknown index. The detailed steps are described in the following algorithm.

Notations used in this paper.

- x = Original signal
- y = Observation vector
- r = Residual error
- M = Input length
- N = Measurement length
- k = Signal sparsity
- R = Residual matrix
- Φ = Measurement matrix (size: $M \times N$)
- λ = Maximum index after dot product
- t = Iterations
- $t_{\max}$ = Required iterations (usually equal to k)
- n = Noise

OMP begins by initializing the residual error to the input measurement vector, selected index set to empty set and initial approximation to a null vector. At iteration t, OMP chooses a new index by finding the best atom matching with the residual, and updates the selected index set. Then, OMP obtains the best-term approximation by a least-squares (LS) minimization.

In OMP, the residue is always orthogonal to all the selected atoms. That means the non-zero correlation will only occur for those atoms, which are not linear combinations of atoms in. Thus at iteration t ,OMP will select an atom which is linearly independent from the previously selected atoms. Therefore, the obvious choice for k-sparse signal recovery is to identify correct atoms in iterations of OMP.

The detail steps of OMP algorithm are described as Table 1.

Table 1. OMP for compressive sensing recovery

OMP Algorithm: $\hat{x} = OMP(y, \Phi)$

Input:

$\Phi \in \mathbb{R}^{N \times d}$ $\quad y \in \mathbb{R}^{N}$ $\quad t_{\max} = k$

Procedure:

Initialize: $r_0 = y, \Lambda_0 = \phi, t = 1$ $\hat{x} = OMP(y, \Phi)$

while $t = M$ is not satisfied

$\lambda_t = argmax_{j=1\ldots N} \left| \left\langle r_{t-1}, \varphi_j \right\rangle \right|$

$\Lambda_t = \Lambda_{t-1} \cup \{ \lambda_t \}$

$\Phi_t = [\Phi_{t-1}, \varphi_{\lambda_t}]$

$\hat{x}_t = argmin \| y\text{-}\Phi_t \hat{x} \|_2$

$r_t = y - \Phi_t \hat{x}_t$, $t = t + 1$

end while

return $\hat{x}(t)$

Output:

$\hat{x}$ $\; r_t \in \mathbb{R}^{N}$

3 Stochastic Gradient Orthogonal Matching Pursuit Algorithm

In this section we discuss OMP algorithm, and extended the idea of OMP to illustrate another recovery scheme called SGOMP and SGOMP(ETT).

The SGOMP algorithm is proposed to divide the CS recovery problem into two processes: pursuing process and estimation process. In the pursuing process, it is desired to identify the location of nonzero terms. In the estimation process, only nonzero terms are calculated. In OMP, the selected matrix of the iteration is related to the LS estimation of last iteration, which leads to the error propagation and makes OMP vulnerable to measurement noise.

The pursuit process of SGOMP and OMP is identical, the correlation of the current residual error and measurement matrix can be calculated to determine the index λ_t :

$$\lambda(t) = \underset{j=1,2,\ldots,N}{argmax}\left|\left\langle r_{t-1}, \varphi_j \right\rangle\right| \quad \textbf{(2)}$$

where N denotes the column number of the measurement matrix. After determining the maximum and selecting the most correlative column, the index set are added as follows:

$$\Lambda(t) = \Lambda(t-1) \cup \lambda(t) \quad \textbf{(3)}$$

The measurement matrix selected according to the index set can then be expressed as follows:

$$\Phi_{\Lambda(t)} = \{\varphi_j \mid j \in \Lambda(t)\} \quad \textbf{(4)}$$

The MMSE equalizer is adopted to address the noise problem in digital communications, as a result, the ZF criterion is often replaced by the MMSE criterion to improve the performance [10].

Since the LS estimation is applied in OMP as well as ZF criterion, it is reasonable to replace LS estimation of OMP algorithm with MMSE criterion, for the AWGN channel, the MMSE solution is expressed as:

$$\hat{x}_{M(AWGN)} = \Phi^*\left(\Phi^*\Phi + \frac{\sigma_n^2}{\sigma_{x|\Lambda}^2} I\right)^{-1} y \quad \textbf{(5)}$$

where $\hat{x}_{M(AWGN)}$ is nonzero terms of $\hat{x}$, $E_{xx}{}^* = \sigma_{x|\Lambda}^2 I_{L\times L}$ and $E_{nn}{}^H = \sigma_n^2 I_{M\times M}$.

However, it is difficult to determine $\sigma_{x|\Lambda}^2$ and σ_n^2 in compressive sensing. In the practical applications, the amplitude of each nonzero term is different and the power of x cannot be controlled. As a result, the $\sigma_{x|\Lambda}^2$ is unavailable. On the other hand, the σ_n^2 is also unknown.

The core idea of the minimum mean square error estimation is to minimize the mean square error of the observation vector y which is identically distributed with x. The gradient descent method is usually used to find the minimum value of the MSE because of the inability to determine the invalid expression of the MMSE estimator. The least mean square estimation is a well-known stochastic gradient descent method, whose purpose is to minimize the mean square error between the observation vector y and the output of the adaptive filter. The steady state solution of the least mean square can be expressed as:

$$\hat{x} = R_x\Phi^*[\Phi R_x \Phi^* + R_n]^{-1} y \quad \textbf{(6)}$$

where $R_n = E_{nn}{}^*$ and $R_x = E_{xx}{}^*$ is the auto correlation matrix of $x_\Lambda = \{x(i) \mid i \in \Lambda\}$. Equation (6) indicates that the LMS estimate converges the iteration to the solution Φ of the MMSE estimate, so that the MMSE estimation can also be realized in the long run even if R_x and R_n have no definite values.

If it further happens that R_n and R_x are nonsingular matrices, then the above equation (6) for x can be rewritten in an equivalent form that will be convenient for later analysis:

$$\hat{x} = [R_x{}^{-1} + \Phi^* R_n^{-1}\Phi]^{-1}\Phi^* R_n^{-1} y \quad \textbf{(7)}$$

The stochastic gradient pursuit algorithm is utilized to iterate the solution of MMSE, and propose a new algorithm named stochastic gradient orthogonal matching pursuit. The compressive sensing (CS) recovery is regarded as a system identification process. If all of the nonzero terms can be identified after iterations, the compressive sensing (CS) without noise n can be modeled in matrix form as:

$$y = \Phi \cdot x = \Phi_{\Lambda} \cdot \hat{x} \tag{8}$$

where the $\hat{x}$ is the optimal nonzero term of x, and Φ_{Λ} is the optimal measurement matrix corresponding to it.

After pursuit process, the selected $M \times L$ optimal matrix $\Phi_{\Lambda(t)}$ is input, and the value of the nonzero term is estimated by the least mean square process. The estimation error of the observation vector y using the adaptive filter can be expressed as:

$$e_{\lambda} = y_{\lambda} - \hat{\Phi}_{\lambda} \cdot \hat{x}_{\lambda} \tag{9}$$

where y_{λ} is the λth element of the observation vector y, $\hat{\Phi}_{\lambda}$ is the λth row of the selected optimal matrix, and the $\hat{x}_{\lambda}$ is a vector, the length of which is $L \times 1$. The gradient decent recursion of least mean square process can be expressed as:

$$\hat{x}_{\lambda+1} = \hat{x}_{\lambda} + e_{\lambda} \cdot \hat{\Phi}_{\lambda}^{*} \tag{10}$$

The output $\hat{x}_M$ of the least mean square process can be expressed as:

$$\hat{x}_M = \hat{x}_{i|\Lambda(t)}(t) \tag{11}$$

After the least mean square process, the current residual error $r(t)$ can be calculated as follows:

$$r(t) = y - \Phi_{\Lambda(t)} \cdot \hat{x}_M \tag{12}$$

where the $\hat{x}_M$ is a $L \times 1$ vector which contains only nonzero terms.

The current residual error's $l2$ norm will approach to zero as the increase of iteration, it can be calculated as:

$$\left\| r^n \right\|_2 = \sum_{i=1}^{M} r_i^2 \tag{13}$$

An early termination scheme is desired reduce the computational complexity of OMP algorithm with early termination threshold is mentioned in [11]. The iterative procedure will be early terminate when the current residual error's norm satisfies:

$$\left\| r^n \right\|_2 < ETT \tag{14}$$

where the early termination threshold ETT is determined by simulation.

Since the root operation for calculating the $l2$ norm requires a high cost, this section presents an optimized early termination criterion that calculates the correlation between the current residual error $r(t)$ and the measurement matrix φ_j, which can be expressed as follows:

$$\eta_t = \arg\max_{j=1,2,\ldots,N} \left| \left\langle r(t), \varphi_j \right\rangle \right| \tag{15}$$

Finally calculate the difference between the current residual error and the degree of correlation of the previous iteration residual error with the measurement matrix ：

$$C(\eta_t, \eta_{t-1}) = \eta_t - \eta_{t-1} \tag{16}$$

The proposed stopping condition is increased on the basis of the number of iterations arriving at M, expressed as:

$$C(\eta_t, \eta_{t-1}) < ETT \tag{17}$$

In order to reduce the number of iterations that are necessary for signal recovery by the SGOMP algorithm while not reducing the performance of the algorithm, how to determine the value of threshold ETT is an important issue.

To look for the value of ETT, we first look into error tolerance margin of the recovered signal, an early termination criterion based on normalized root-mean-squared error (NMSE) is proposed in this paper, which is denoted as E . In practical applications, the recovery can be regarded as successful recovery if NMSE of the recovered signal is lower than targeted NMSE as:

$$E_{NMSE} = \sqrt{\frac{\sum_{t=1}^{N}(\hat{x}_t - x_t)}{N}} \tag{18}$$

where x_t and $\hat{x}_t$ are *ith* element in x and $\hat{x}$.

The recovered signal $\hat{x}$ does not need to be exactly the same as x in noiseless scenario. The equation (18) can be expressed as:

$$E_{NMSE}{}^2 \times N > \sum_{t=1}^{N}(\hat{x}_t - x_t) \tag{19}$$

According to Cauchy-Schwarz inequality, the early termination threshold ETT can be expressed as:

$$ETT = E_{NMSE}{}^2 \times N^2 \tag{20}$$

The proposed SGOMP algorithm will stop when the proposed stopping condition is smaller than the threshold ETT or when the set maximum number of iterations is reached. Otherwise, the SGOMP algorithm will go back to calculation of correlation and algorithm iterates.

The detail steps of SGOMP algorithm can be described as Fig. 2.

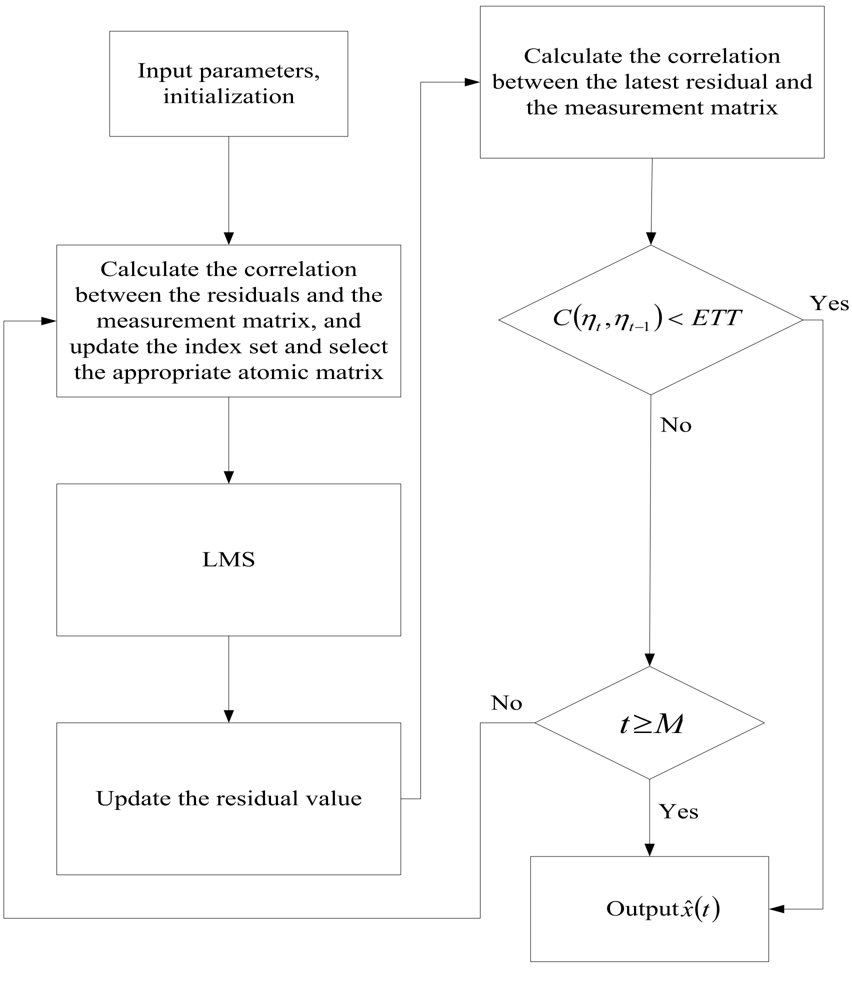

Fig. 2. The flowchart of the SGOMP algorithm

4 Numerical Experiments

In this section, we conduct an experiment on SGOMP and OMP algorithms under noisy scenario, the simulation setup is summarized as follows: The input length N=512, measurement length M=64, and signal sparsity K=8 are set according to [12]. We modify the signal-to-noise ratio (SNR) to observe the recovery performance. The K_{max} is set to be 16, and maximum number of iterations is set to be 64 as OMP. When $E = 0.5\times10^{-3}$ the early termination threshold ETT can be determined $ETT = 6.6\times10^{-2}$ according to (20). Due to additive noise n, the required iterations of OMP cannot be determined. Therefore, the halting condition of OMP algorithm is $\left\|r^n\right\|_2 < 0.5\times10^{-3}$. Respectively, if E_{NMSE} is less than , the trial is regarded as successful recovery.

The SNR (in dB) is defined as:

$$SNR = 10log_{10}\frac{\left\|\Phi\cdot x\right\|_2^2}{\left\|n\right\|_2^2} \tag{21}$$

4.1 Signal Recovery Performance under Noisy Scenario

Fig. 3 shows the simulation results of the signal recovery rate of the traditional OMP algorithm, ROMP algorithm, BP algorithm, CoSaMP algorithm and the SGOMP correlation algorithms proposed in this paper. SGOMP (ETT) represents the SGOMP algorithm using the early termination threshold.

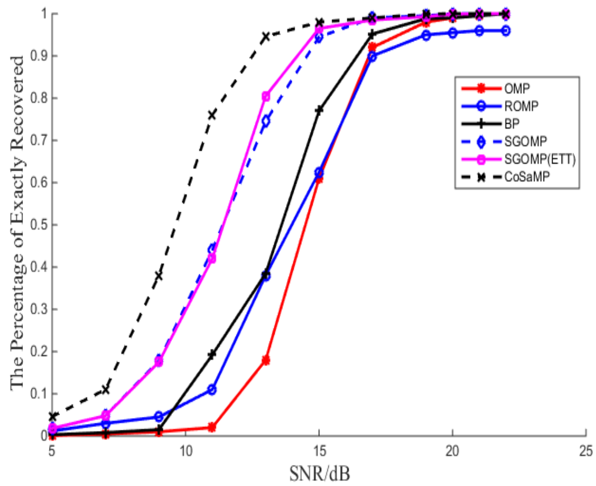

Fig. 3. Successful recovery rate of SGOMP, SGOMP(ETT), OMP, ROMP, BP, and CoSaMP

It can be observed that the proposed SGOMP algorithm is robust to noise than OMP algorithm. With the increase of signal-to-noise ratio (SNR), the original signal recovery probability of SGOMP algorithm and the other algorithms are increasing constantly, but the growth rate of which is different with each other obviously. When the SNR is 5dB, the difference of the recovery performance between these algorithms is small, the recovery rate is very small. With the SNR increase, the recovery performance of SGOMP algorithm is much better than the traditional OMP algorithm and the other algorithms discussed in this section expect CoSaMP algorithm. When the SNR increased to 15dB, the recovery rate of SGOMP(ETT) algorithm is almost 1, which is about 35% higher than that of OMP algorithm, about 34% higher than that of ROMP algorithm and about 19% higher than that of BP algorithm. Especially, the CoSaMP algorithm performs much better than any other algorithms compared in this section when the sparse information is available. In practical, the sparse information used to be unavailable for practical applications, as a result, it can not be compared with other algorithms here. Therefore, the SGOMP algorithm proposed in this paper is much stronger than that of the traditional OMP algorithm in the noise environment. In addition, it can be observed that the recovery rate of SGOMP (ETT) using the early termination threshold remains almost at the same level as SGOMP as the SNR increases, so the use of early termination threshold does not have a significant impact on the performance of the SGOMP algorithm.

4.2 The Number of Iterations Required for Signal Recovery

The analysis of required iterations of proposed algorithms and OMP algorithm are shown in Fig. 4, where SGOMP (ETT) represents the SGOMP algorithm using the early termination threshold ETT. We average iteration counts of simulated 100000 trials for each algorithm.

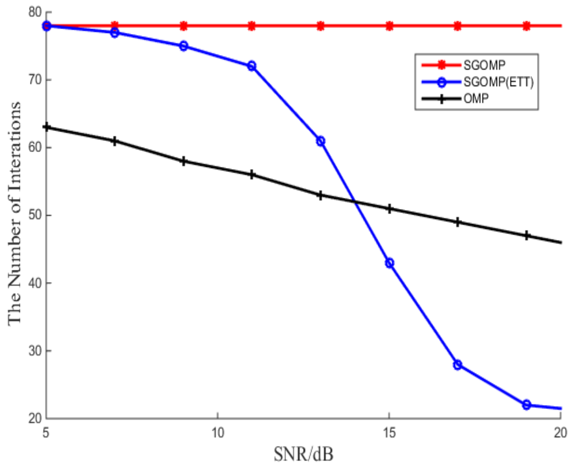

Fig. 4. Analysis of required iterations for OMP and SGOMP-related recovery algorithms

It can be observed that required iterations of SGOMP without early termination threshold is more than OMP regardless of the value of the SNR, and the required iterations of SGOMP algorithm does not change with the increase of SNR, on the contrary, the required iterations of SGOMP (ETT) and OMP decreases with the increase of SNR, the required iterations of the SGOMP (ETT) algorithm is more than that of the OMP algorithm when the SNR is low. The number of iterations of SGOMP (ETT) algorithm is higher than that of OMP algorithm in SNR environment. However, with the increase of SNR, the required iterations of SGOMP (ETT) algorithm is much more than which of traditional OMP algorithm. Due to proposed early termination scheme, it can be observed that required iterations of SGOMP and SGOMP (ETT) decrease dramatically when SNR is higher than 11 dB. On the other hand, the required iterations of proposed algorithms are less than OMP when SNR is higher than 14 dB. The early termination scheme is able to reduce 47% and 72% iterations in SGOMP when SNR equals 15 dB and 19 dB, respectively. According to the simulation results of the success rate and the required iterations, we can conclude that the SGOMP algorithm with the early termination threshold ETT can reduce the required iterations almost without affecting the success rate of original signal recovery.

5 Conclusion

The results of numerical experiments reveal that the proposed algorithms have a higher success rate of original signal recovery in noisy environment. In addition, the use of the early termination threshold (ETT) can reduce the complexity of the proposed algorithm without affecting the success rate of original signal recovery.

Acknowledgements

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References

[1] W. Zhang, Z. Zhang, H.-C. Chao, Cooperative fog computing for dealing with big data in the internet of vehicles: architecture and hierarchical resource management, IEEE Communications Magazine 55(12)(2017) 60-67.

[2] Z. Tian, G.B. Giannakis, Compressed sensing for wideband cognitive radios, in: Proc. IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP ’07, 2007.

[3] Z. Tian, Y. Tafesse, B.M. Sadler, Cyclic feature detection with sub-Nyquist sampling for wideband spectrum sensing, IEEE Journal of Selected topics in signal processing 6(1)(2012) 58-69.

[4] F. Zeng, C. Li, Z. Tian, Distributed compressive spectrum sensing in cooperative multihop cognitive networks, IEEE Journal of Selected Topics in Signal Processing 5(1)(2011) 37-48.

[5] Z. Zhang, C.-F. Lai, H.-C. Chao, A green data transmission mechanism for wireless multimedia sensor networks using information fusion, IEEE Wireless Communications 21(4)(2014) 14-19.

[6] D.L. Donoho, Compressed sensing, IEEE Transactions on Information Theory 52(4)(2006) 1289-1306.

[7] M.A. Figueiredo, R.D. Nowak, S.J. Wright, Gradient projection for sparse reconstruction: application to compressed sensing and other inverse problems, IEEE Journal of Selected Topics in Signal Processing 1(4)(2007) 586-597.

[8] J.A. Tropp, A.C. Gilbert, Signal recovery from random measurements via orthogonal matching pursuit, IEEE Transactions on Information Theory 53(12)(2007) 4655-4666.

[9] D. Needell, R. Vershynin, Uniform uncertainty principle and signal recovery via regularized orthogonal matching pursuit, Foundations of Computational Mathematics 9(3)(2009) 317-334.

[10] S.S. Haykin, Adaptive Filter Theory, 4th ed., Pearson Education India, New Delhi, 2008.

[11] J.A. Tropp, S.J. Wright, Computational methods for sparse solution of linear inverse problems, Proceedings of the IEEE 98(6)(2010) 948-958.

[12] J.L. Stanislaus, T. Mohsenin, High performance compressive sensing reconstruction hardware with QRD process, in: Proc. 2012 IEEE International Symposium on Circuits and Systems (ISCAS), 2012.