Wireless Pers Commun
DOI 10.1007/s11277-015-3156-x

Compressive Frequency Hopping Signal Detection Using Spectral Kurtosis and Residual Signals

Chenlin Hu[1] · Jin Young Kim[1] · Seung You Na[1] · Hyoung-Gook Kim[2] · Seung-Ho Choi[3]

Abstract Over the last decade, the frequency hopping (FH) detection has attracted a great deal of interest due to its effectiveness. In general, FH adopts the concept of changing a carrier frequency following a random sequence which is only known by a transmitter and a receiver. In order to detect this unknown signal and determine its component of frequency hop, this project aims to take advantage of Compressive Sensing for sparse signal in frequency domain. Spectral kurtosis is firstly calculated to identify peak locations which represent hopping frequency. Then the most optimal peaks are selected by applying Compressive Sensing Match Pursuit algorithm to overcome noise uncertainty. The hop time is finally obtained from the residual between the given signal and the estimated one. The experiment results show that the system performs effectively even when SNR values are below −10 dB, and the presented approach can effectively detect the hopping time. Compared to other conventional approaches, our proposed method is appropriate for lower and more widely varying SNR and also considerably reduces the complexity.

Keywords Compressive sensing · Spectral kurtosis · Peak detection · CoSaMP · Residual signal

✉ Jin Young Kim
beyond@jnu.ac.kr

[1] Department of Electronics and Computer Engineering, Chonnam National University, 300 Yongbong-dong, Buk-gu, Gwangju 500-757, Republic of Korea

[2] Kwangwoon University, Seoul, Republic of Korea

[3] Department of Computer, Dongshin University, Naju, South Korea

Published online: 21 December 2015

1 Introduction

Frequency-hopping spread spectrum (FHSS) is a method which employs a pseudo-random sequence known by both a transmitter and a receiver to transmit radio signals with rapidly switching a carrier among many frequency channels. Frequency hopping (FH) technique is adopted for communication security, which is an essential issue in various fields, especially in military and business transactions. As mentioned in [1], FHSS is widely adopted in tactical communications due to its low probability of detection and interception, agility, and robustness to jamming. Estimating and tracking the parameters are important issues in the applications of both military and civilian domains: from interception of non-cooperative communications, to collision avoidance and cognitive radio.

In general, FH adopts the concept of changing a carrier frequency following a random sequence which is only known by a transmitter and a receiver. Therefore, in practice as stated by Aydh and Polydoros [2], the hopping parameters, hopping time and frequency, should be estimated by a receiver. During FH signal detection, the signal modeling is defined as:

$$x(t) = \sum_{k} rect_{T_H}(t - kT_H - \alpha T_H) \exp[j2\pi f_k(t - kT_H - \alpha T_H)], \tag{1}$$

where $0 < \mathrm{t} \leq T$, $rect_{T_H}$ is the window whose length is T_H, in $[0, T_H]$ is 1, and 0 in otherwise. f_k is the hopping frequency, T_H is hopping interval, αT_H is hopping timing deviation. Usually hopping frequency f_k is integer multiples of $1/T_H$, in order to meet the orthogonal frequency hopping between different characteristics. For the estimation of the parameters of FH signal, such as hop rate, frequency, timing, period, instant and signal power, vast efforts have been made to study the methods [3]. Among many methods as introduced in [4], the Short-Time Fourier Transform (STFT) analyzing method [5] is simple, but cannot satisfy the performance of time and frequency resolution and frequency at the same time. The Wigner spectrum [6] method and suppressing power spectrum method [7] are only well used in higher SNR. The performance is not so good when SNR is not high enough. Furthermore, Wavelet-transform method, Gabor spectrum method [8], Wigner-Ville distribution [9], and array signal processing method [10] are also great tools for dealing with FH signals. Meanwhile, Yuan et al. [11] proposed a novel algorithm that takes advantage of compressive sensing (CS) for the sparse signal in frequency domain, where the peak represents hopping frequency. By calculating cosine of angles between incoherent measurements and column of Gaussian matrix, the maximum value indicates the position of hopping frequency. On the other hand, the blind detection [12] is used to determine the occurrence of frequency hop, accomplished by statistically analyzing the deviation between actual sampling values and the expectation.

In this paper, we present a new approach of detecting signal's hopping frequency and time. We first select the most optimal peaks by calculating kurtosis and applying Compressive Sampling Match Pursuit (CoSaMP) algorithm [13], which is an enhancement of OMP. After that, the hop time can be obtained from the residual between the given frequency-domain signal and the estimated ones. Experimental results have proven that the presented approach can be applied under noisy environments whose SNR is higher than −10 dB. Compared to other traditional approaches mentioned in [7, 8], our proposed method, without measuring the energy of peaks, can be applied for lower and more widely varying SNR, and also considerably reduces the complexity.

2 Frequency Components Detection

2.1 Spectrum Peaks Detection

Let's consider a discrete-time signal x of N length and an orthonormal basis Ψ such as Fourier basis F [14, 15]. Then signal x can be expressed as $x = \Psi s$, where s is the transformation of x. The compressed signal can be modeled as,

$$y = \Phi x = \Phi F^{-1} s = \Theta s, \tag{2}$$

where the normalizing matrix F^{-1} is given by.

$$F^{-1}(k, l) = \frac{1}{\sqrt{N}} e^{j\frac{2\pi}{N}kl} \tag{3}$$

When the signal is made of randomly selected M numbers of samples from 0 to $N - 1$, which are denoted as t_k satisfying.

$$0 \le t_1 < t_2 < \cdots < t_k < \cdots < t_M \le N - 1 \tag{4}$$

as the time samples that are strictly distinguished. Then sampling can be expressed using the matrix ϕ of.

$$\Phi(k, l) = \begin{cases} 1 & , if t_k = 1 \\ 0 & , otherwise \end{cases}. \tag{5}$$

Also Θ are random-sampling matrix and measurement matrix of $\Theta = \phi\, F^{-1}$. After that, the peak candidates are generated by adopting the frequency-domain information of $\breve{s} = F\breve{y}$, where F is Fourier transform matrix, $\breve{y}$ is the extended version of y and $\breve{y}(n)$ is zero when n is not elements of CS time instances. An example of weighting coefficient $\breve{s}_l$ is illustrated in Fig. 1.

The distinct peaks in frequency-domain can be clearly observed in Fig. 1 under preferable SNR. Then based on the signal energy detection, the number of peaks can be obtained. However, measuring the variance of noise (from time-domain and CS) and

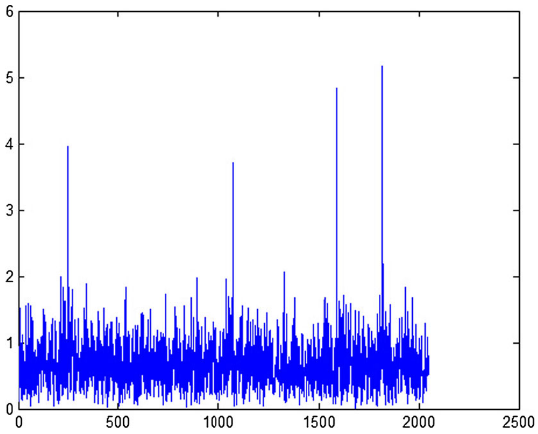

Fig. 1 The absolute value of $\breve{s}_l$ (CS rate 0.15, 5 frequencies components)

determining the threshold is not that simple. Consequently, a method to measure noise and independent peaks is employed.

Instead of exploring the peakedness based on Rayleigh distribution, we separately analyze the frequency in real and imaginary parts because Gaussian noise exists in both these two components independently. Figure 2 depicts the division process of $\breve{s}_l$ of signal from Fig. 1. Apparently, the peaks in each component are more distinctive than that of the complex one. Therefore, we used the Kurtosis for each part separately and combine them either by l_1 or $l\infty$-norm Fig. 3.

2.2 Kurtosis Calculation

Kurtosis is a measurement of the peakedness which describes the slope of candidates. It is formally defined as the standardized fourth population moment about the mean [16],

$$\beta_2 = \frac{E\left[(X-\mu)^4\right]}{\left(E\left[(X-\mu)^2\right]\right)^2} = \frac{\mu_4}{\sigma^4} \tag{6}$$

where E is the expectation operator, μ is the mean, μ_4 is the fourth moment about the mean, and σ is the standard deviation. The normal distribution has a kurtosis of 3, and $\beta_2 - 3$ is often explained as a correction to make the kurtosis of distribution equal to zero ($\beta_2 - 3$ is sometimes denoted as γ_2). A sample counterpart to β_2 can be obtained by replacing the population moments with the sample moments, which gives

$$b_2 = \frac{\sum\left(X_i - \overline{X}\right)^4/n}{\left(\sum\left(X_i - \overline{X}\right)^2/n\right)^2}, \tag{7}$$

where b_2 is the sample kurtosis, $\overline{X}$ is the sample mean, and n is the number of observations.

In our problem the main frequency components are expressed under sharp peaks in real part, as well as the imaginary one. In addition, calculating kurtosis for each of the 2048 candidates may lead the peaks to less contribution and increase the detection complexity. Therefore, we separate signal to 16 blocks; each has 128 samples.

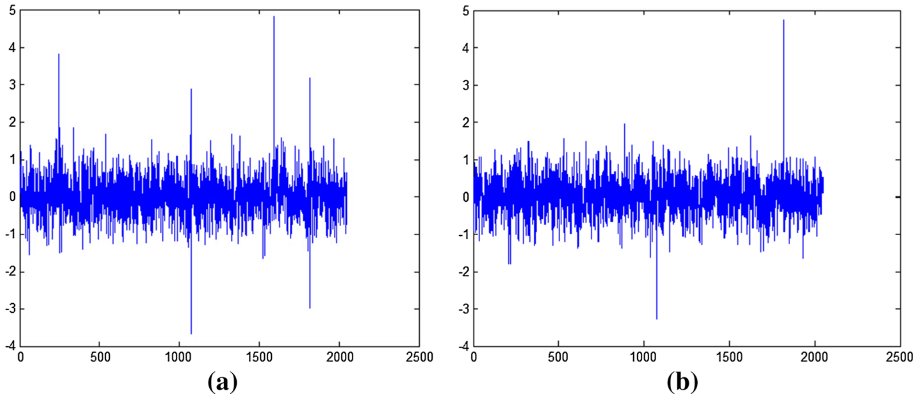

Fig. 2 Real and imaginary parts of $\breve{s}_l$. **a** Real part **b** Imaginary part

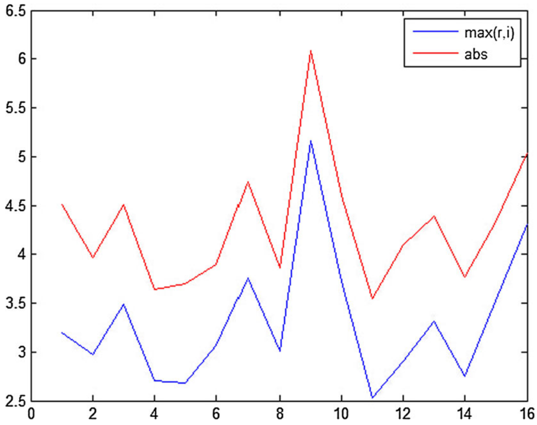

Fig. 3 Comparison of l_1 or l_∞-norm

2.3 Determine Value of K

With the determined threshold, in order to choose peaks as candidates which are higher and over the threshold, we will take the following steps.

(a) Firstly, we divide $\breve{s}_l$ into $Q = 16$ blocks and each block can be expressed as $\breve{s}_q, q = 1, 2, \ldots Q$.
(b) After that, an empty vector w for each block and a set P for storing peaks are initialized.
(c) We calculate the kurtosis of each w vector. If it is smaller than the adaptive threshold, move to step (e) and stop. Otherwise, we insert the value and position of the maximum w to set P. Then the value at w position is changed to zero.
(d) We repeat step (c) to collect other peaks in qth block.
(e) Output set P.

Finally K peaks are chosen as displayed in Fig. 4 without noise. Although kurtosis can determine spectral peaks, the detected candidates still encounter some false positive, which is caused by the perturbation of high SNR noise. Therefore, we only utilize the

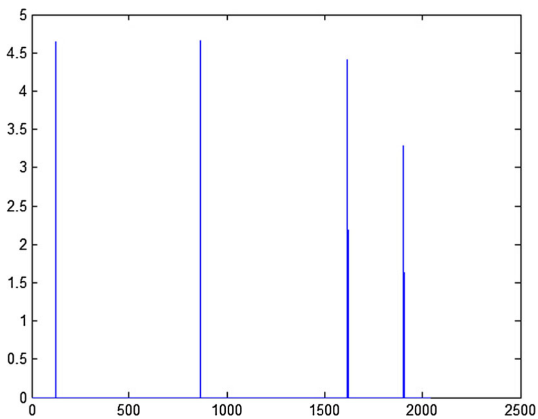

Fig. 4 K chosen peaks

number of peaks K at this stage. The exact positions of peaks are chosen by CoSaMP algorithm.

3 Frequency Hopping Time Detection

3.1 Choose Optimal Peaks using CoSaMP

CoSaMP is a recovery algorithm extended from OMP (Orthogonal Matching Pursuit), which generates an approximation by locally optimizing choices at each of the iterations, and applying CS theorm. As explained by Needell and Tropp [17], based on CS concept, CoSaMP employs only a small nonadaptive samples, which contain plentiful information to sufficiently approximate the original signal.

According to [18], the challenging task remains in identifying the locations of the strongest frequency components in the target signal. Therefore, for a given s-sparse signal x, sampled using the matrix ϕ, the largest components with the largest energy will be spotted first. This process is repeated until the residual converges to ε. Then $y = \Phi * \Phi x$ is the approximation of x. During the approximation in each step, the error which is relative

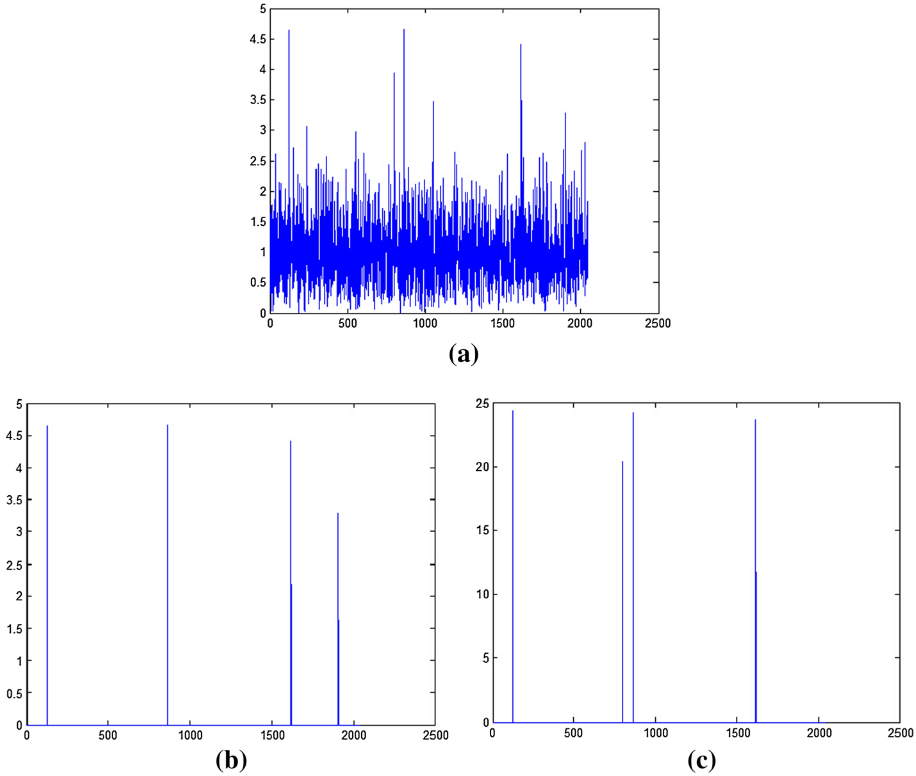

Fig. 5 The effect of applying CoSaMP **a** $\breve{s}_l$ with strong noise **b** wrongly detected peaks **c** Rechosen peaks by CoSaMP

to the unrecoverable energy υ increases. This is because of either noise in the samples or the signal, which is not sparse.

$$\upsilon = \|x - x_s\|_2 + \frac{1}{\sqrt{s}}\|x - x_s\|_1 + \|e\|_2 \tag{8}$$

Taking this method for an application, given the desired number of peaks for example K, the algorithm will choose 2 K candidates to avoid missing detection. Then the K optimal ones will be selected as shown in Fig. 5.

3.2 Residual Analysis

With the K detected peaks, the approximated signal can be reconstructed. Nevertheless, we are only interested in detecting the hopping time. Therefore, instead of reconstructing the signal, we have measured the residual between approximation frequencies and the ordinary one.

The two-sparse signal whose frequencies are q_1 and q_2 are taken as an example, the signal modeling is as follows:

$$y_2(k) = Ae^{j\frac{2\pi}{N}kq_1}(u(k) - u(k - N_1)) + Ae^{j\frac{2\pi}{N}kq_2}(u(k - N_1) - u(k - N)) + \eta(k), \tag{9}$$

where A is amplitude, N is the length of signal, and N_1 is hop time. We assume the measured signal's amplitude is $\breve{A}$. Then the approximated signal is expressed as,

$$\breve{y}_2(k) = \breve{A}e^{j\frac{2\pi}{N}kq_1}. \tag{10}$$

So the residual is

$$\begin{aligned} \mathrm{r}(k) &= y_2(k) - \breve{y}_2(k) \\ &= Ae^{j\frac{2\pi}{N}kq_1}(u(k) - u(k - N_1)) + Ae^{j\frac{2\pi}{N}kq_2}(u(k - N_1) - u(k - N)) + \eta(k) - \breve{A}e^{j\frac{2\pi}{N}kq_1} \\ &= \left(A - \breve{A}\right)e^{j\frac{2\pi}{N}kq_1}(u(k) - u(k - N_1)) + A\,e^{j\frac{2\pi}{N}kq_2}(u(k - N_1) - u(k - N)) \\ &\quad - \breve{A}e^{j\frac{2\pi}{N}kq_1}(u(k - N_1) - u(k - N)) + \eta(k) \end{aligned} \tag{11}$$

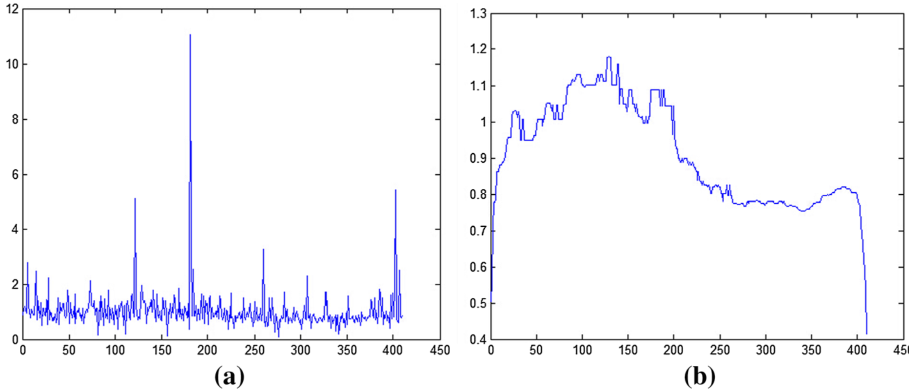

Fig. 6 The median filter effects to residuals. **a** Residual without median filter **b** Residual with median filter

From the equation above, the residual is reduced in time [0, N_1]; otherwise it is increased in [$N_1 + 1$, N] compared with the power of original signal. For $y(k)$ is the CS signal, $rr(k)$ is the residual, then the index $rr(k)$ is utilized in the research.

$$rr(k) = \frac{|r(k)|}{|y(k)|} \tag{12}$$

In addition, we applied the median filter described in [19] with rr to enable efficient crossing point detection. The impacts of this procedure are shown in Fig. 6. The unfiltered residual, on the left side, is extremely noisy, which makes it impossible to detect the intersection. Otherwise, the one on the right including the median filter shows much enhancement. A conclusion can be deduced by observing the residual of specific frequency. Whether the hopping occurs in this frequency, the residual will be separated into two distinct segments surrounding hopping time. One part has a larger error, indicating the absence of this frequency, while the other tends to be much smaller.

In a certain case, $rr(k)$ is shown in Fig. 7. Figure 7 illustrates the residual collected by adopting our proposed method. Obviously, there are four lines representing four distinct frequencies. Moreover, two of them intersect each other at the crossing point whose amplitude is around one. In conclusion, Fig. 7 describes the case of compressing four frequencies signal, and the hopping time stays at the crossing point.

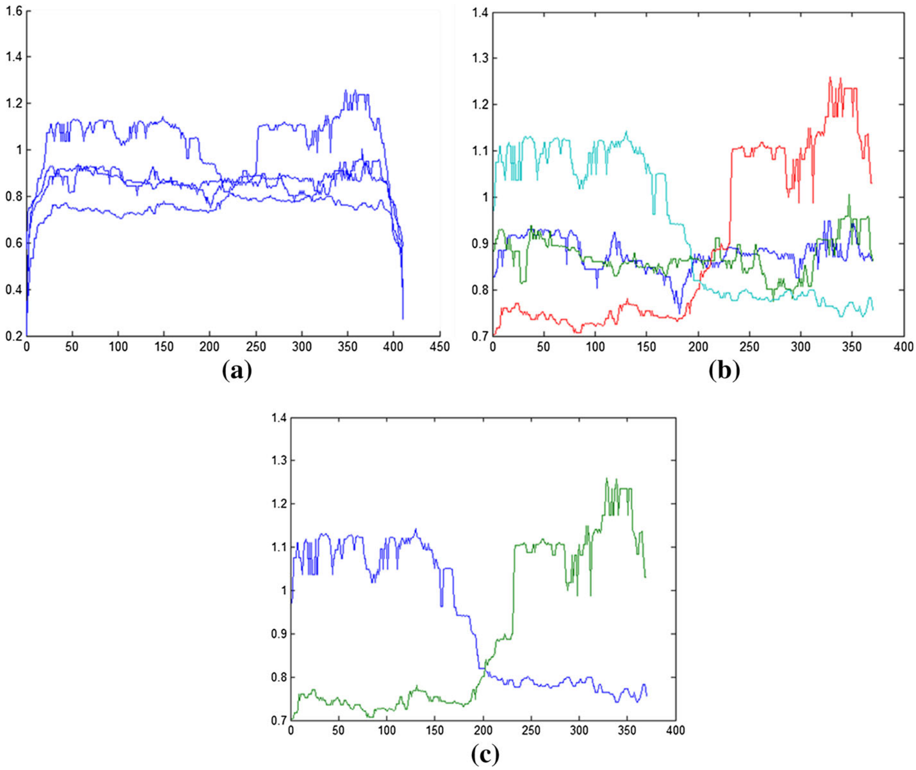

Fig. 7 Residuals of approximation and original signal **a** $rr(k)$ of 4-sparse signal **b** $rr(k)$ without edge **c** two hopping frequency components

Given detected frequencies, we apply the CS approach to its corresponding signal. Residual is the difference between the CS signal and the estimated one. Then the result lines which represent residual have two statuses, hopped or not. For one thing, the not hopped one means frequency is constant from the beginning to the end, so the line will be flat. On the other hand, if frequency hopped from one to another, there will be a slope. For The part with this frequency, the line is low. On the contrary, for the part without this frequency, the line of residual will be high.

For this four-sparse signal, it includes two constant frequencies and other two frequencies hopped from one to the other. The two relative flat lines, which are blue and green in Fig. 7b, represent two constant frequencies of this signal. Meanwhile, the cyan and red ones are sloped and crossing, each of them has high and low parts because of signal hopping. Based on this, we choose these two hopped frequency components, which are blue and green in Fig. 7c for analysis.

After noticing this, we attempt to find the crossing point of the two lines. The two lines with a larger difference will be selected following Eq. (2). Their crossing point has the smallest difference of these two lines.

$$\left[i_{cand}, j_{cand}\right] = \arg\max \left| \max_{i \in [1,3]} i - \min_{j \in [i+1,4]} j \right| \tag{13}$$

4 Experiments and Results

To demonstrate the efficiency of our proposed approach, we conduct the experiments that qualify our proposed approach for detecting hopping time under various noise models. The simulation is based on a four-sparse FH signal, where length is 2048, compressed with 0.15 CS rate and the hopping time is 1024.

We divide our qualification procedure into two steps due to the dependence of hopping time and the number of frequency. The purpose of our first experiment is to analyze an adequate SNR which allows our method to successfully detect the hopping time. Then, the

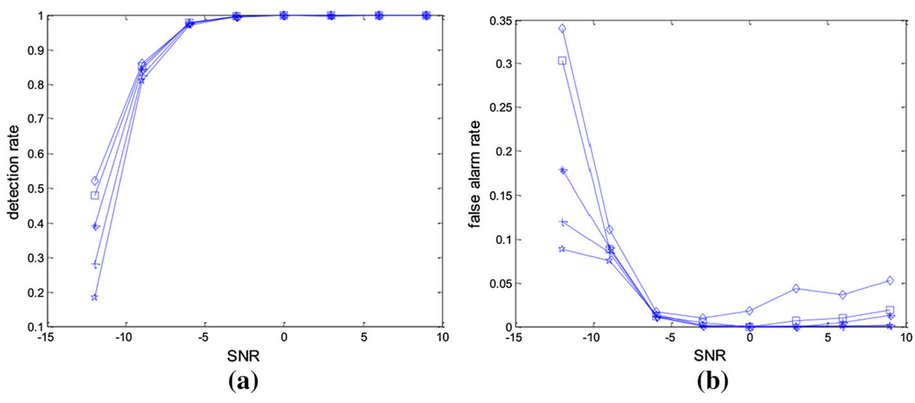

Fig. 8 Evaluation of number of blocks and experiment results (Pentagram:2, Plus:4, Star:8, Square:16, Diamond:32). **a** DR of 2-sparse signal **b** FAR of 2-sparse signal

precision of hopping time estimation with regards to those feasible SNR is further explored in the second step.

4.1 Evaluation of Detection Parameters

In this section, we evaluate the number of bands/blocks, CS rate, with K-sparse signal in a different SNR environment. We carry out the evaluation for one parameter at a time, and fix the other parameters to the default values, test for detection rate and false alarm rate with SNR range from −15 to 10 dB.

With respect to the number of bands, Fig. 8a and b present different results obtained by utilizing various bands in peak localization. Specifically, with SNR higher than −6 dB, the accuracy is not affected by the number of blocks. Otherwise, under the low SNR, only the long block for example 32 or 16-components can carry the best performance but it also increases the false alarm.

As observed in Fig. 9a–d, for both the two-sparse and four-sparse cases, the increment of samples results in better performance with a higher CS rate. And at SNR higher than −6 dB, the false alarm rate reaches to 0.001. The most efficient CS rate is 0.15 which is proven in [11]; however, in our experiments, the most effective CS rate is 0.2, which not only reduces measurements but also can obtain a high detection rate.

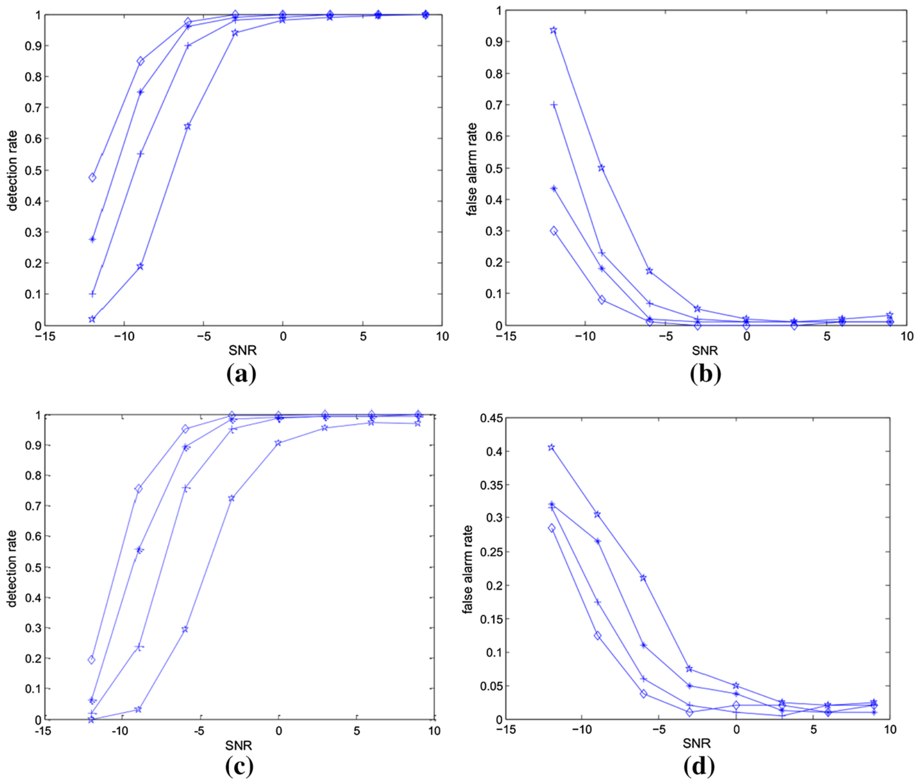

Fig. 9 Evaluation of CS rate and experiment results (Pentagram:0.1, Plus:0.15, Star:0.2, Diamond:0.25). **a** DR of 2-sparse signal **b** FAR of 2-sparse signal **c** DR of 4-sparse signal **d** FAR of 4-sparse signal

We show results for the signals which have different number of frequencies in Fig. 10a and b. When there are more frequencies in the signal, it can be detected better, but with lower accuracy. This situation appears when SNR is lower than −6 dB which has strong noise for annoying detection.

4.2 Hopping Times Detection

4.2.1 Detection Rate

We divide our qualification procedure into two steps due to the dependence of hopping time and the number of frequency. The purpose of the first experiment is to analyze an adequate SNR, which allows our method to successfully detect the hopping time. Then, the precision of hopping time estimation with regards to those feasible SNR is further explored in the second step.

According to Table 1, our method can perfectly localize the hopping time derived from signal with SNR larger than or equal to −10 dB. The poor performance that hopping time cannot be detected only appears under the extremely noisy environments such as SNR smaller than −15.

4.2.2 Precision of Detection

For further justification, we also explore the precision of the proposed method under the appropriate frequencies. The precision measurement is acquired using Eq. (14) and the results are explained in Table 2.

$$\Pr ecision = 1 - \frac{|Detected\ hopping\ point - 1024|}{1024} \times 100\% \tag{14}$$

The obtained results have proven that our approach can precisely detect hopping time in environments with SNR higher than -10 dB. During the experiments, even SNR drops below −10 dB, which has only 30.77 or 15.38 % in detection rate, and the estimated hopping times are always close to 1024.

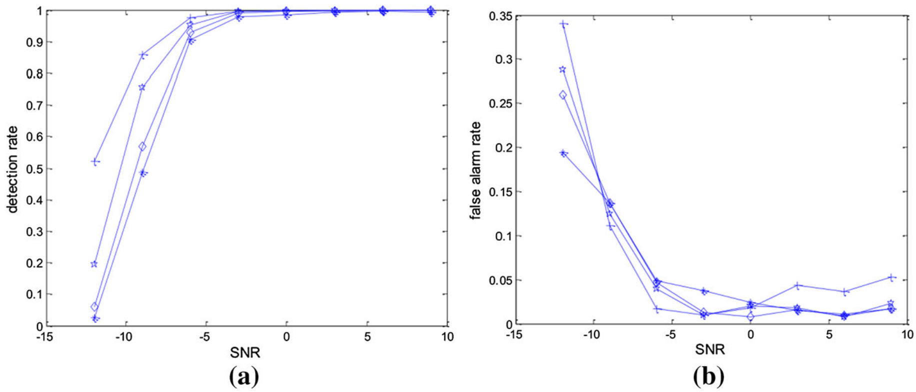

Fig. 10 Evaluation of K-sparse signal and experiment results (Plus:2, Pentagram:5, Diamond:8, Star:10) **a** DR of K-sparse signal **b** FAR of K-sparse signal

Table 1 Hopping time detection rate with different SNR

SNR	−20	−15	−10	−5	0	5
Detection rate	15.38 %	30.77 %	100 %	100 %	100 %	100 %

Table 2 The precision of hopping time detection

SNR	−10	−5	0	5	10
Precision	99.76 %	99.81 %	99.85 %	99.82 %	99.84 %

5 Conclusions

This study proposes a method to detect hopping time and frequency in frequency hopping signal using kurtosis and CoSaMP algorithm. Firstly, we compress the signal by Compressive Sensing method with CS rate of 20 %, and calculate kurtosis of each block which has the length of 128. Secondly, based on the results of kurtosis, we determine the number of frequencies K, and apply CoSaMP algorithm for selecting K optimal peaks from the given signal. Finally, the hopping time is obtained by analyzing the residual between approximation frequencies and the ordinary one.

Experimental results show that the proposed method offers better performance with a higher CS rate. The most efficient CS rate is 0.15, which is proven in a mathematical way; however, in our experiments, the most effective CS rate is 0.2, which not only reduces measurements but also can obtain a high detection rate. For the number of bands determination, with SNR higher than −6 dB, the accuracy is not affected by the number of bands. Otherwise, under the low SNR, only the long band for example 32 or 16-components can carry the best performance but it also increases the false alarm. Furthermore, when there are more frequencies in this signal, it can be detected better, but with lower accuracy.

The results obtained during the detection experiments depict that the hopping time is 100 % detected in the environment where SNR is higher than −10 dB and that the precision rate reaches 99.8 %.

Currently, this method is well used in detecting the hopping time of FH signal, and is comparable to other traditional approaches. Our proposed method without measuring the energy of peak can be applied for lower and more widely varying SNR and also can reduce the complexity considerably. Our future work will consider combining this method with others to enhance the accuracy and accomplish better utilization in a low SNR situation.

Acknowledgments This work was supported by the ICT R&D program of MSIP/IITP [11-911-01-112, Technology Development for the My-F Convergence Service].

References

1. Angelosante, D., Giannakis, G. B., & Sidiropoulos, N. D. (2010). Estimating multiple frequency-hopping signal parameters via sparse linear regression. *IEEE Transaction on Signal Processing, 58*, 5044–5056.
2. Aydh, L., & Polydoros, A. (1996). Hop-timing estimation for FH signals using a coarsely channelized receiver. *IEEE Transaction on Communications, 44*(4), 516–526.

3. Sha, Z.-C., Liu, Z.-M., Huang, Z.-T., & Zhou, Y.-Y. (2013). Online hop timing detection and frequency estimation of multiple FH signals. *ETRI Journal, 35*, 748–756.
4. Zeng, Y., Liu, X., & Li, O. (2011). A new method of frequency-hopping (FH) signal detection. *Journal of Electronics (China), 28*, 468–473.
5. Chung, C.D., & Polydoros, A. (1991). Detection and hop-rate estimation of random FH signals via autocorrelation technique. In *Proceedings of MILCOM '91* (Vol. 1, pp. 345–349).
6. Chung, C. D., & Polydoros, A. (1995). Parameter estimation of random FH signals using autocorrelation techniques. *IEEE Transaction on Communications, 43*, 1097–1106.
7. Barbarossa, S., & Scaglione, A. (1997). Parameter estimation of spread spectrum frequency-hopping signals using time-frequency distributions. In *Proceedings of first IEEE Signal Processing Workshop on Signal Processing on Advanced Wireless Communication* (pp. 213–216). Paris: IEEE.
8. Mallat, S. G., & Zhang, Z. (1993). Matching pursuits with time–frequency dictionaries. *IEEE Transaction on Signal Process*, *41*, 3397–3415.
9. Fan, H., Guo, Y., & Feng, X. (2008). Blind Parameter Estimation of Frequency Hopping Signals Based on Matching Pursuit. In *Proceedings of 4th International Conference on Wireless Communication, Networking and Mobile Computing* (pp. 1–5).
10. Ko, C. C., Zhi, W., & Chin, F. (2005). ML-based frequency estimation and synchronization of frequency hopping signals. *IEEE Transacton on Signal Processing, 53*, 403–410.
11. Yuan, J., Tian, P. W., & Yu, H. Y. (2009). The identification of frequency hopping signal using compressive sensing. *Scientific Research Communications and Network, 1*(1), 52–56.
12. Wu, J., Liu, N., Zhang, Y., & Shen, C. (2012). Blind detection of frequency hopping signal based on compressive sensing. In *Proceedings of 2nd International Conference on Consumer Electronics, Communication and Networks* (pp. 1691–1694). Yichang: IEEE.
13. Needell, J. A. T. D. (2009). CoSaMP: Iterative signal recovery from incomplete and inaccurate samples. *Applied and Computational Harmonic Analysis, 26*(3), 301–321.
14. Sirotiya, M., & Banerjee, A. (2010). Detection and estimation of frequency hopping signals using wavelet transform. In *Proceedings of 2nd UK–India-IDRC International Workshop on Cognitive Wireless Systems* (pp. 1–5).
15. Yu, N., & Li, Y. (2013). Deterministic construction of Fourier-based compressed sensing matrices using an almost difference set. *EURASIP Journal of Advanced Signal Processing, 2013*(1), 1–14.
16. DeCarlo, L. T. (1997). On the meaning and use of kurtosis. *Psychological Methods, 2*, 292–307.
17. Needell, D., & Tropp, J. A. (2009). CoSaMP: Iterative signal recovery from incomplete and inaccurate samples. *Applied and Computational Harmonic Analysis, 26*, 301–321.
18. Chenlin, Hu, & Kim, Jin Young. (2015). Spectral domain noise modelling in compressive sensing-based tonal signal detection. *IEICE Transaction on Fundamentals of Electronics Communications and Computer Sciences, 98*(5), 1122–1125.
19. Samsonov, A. A., & Johnson, C. R. (2004). Removal of intensity bias in magnitude spin-echo mri images by nonlinear diffusion filtering. *Proceedings of SPIE, 5370*, 232–242.

Chenlin Hu is graduated as a M.S. degree from dept. of Electronics and Computer Engineering, Chonnam National University. She received the B.S. degree in Harbin University of Science and Technology in 2013. Her research interests include signal processing. Now she is working in China Mobile Communication Corp.

Jin Young Kim received B.S. degree, M.S. degree and Ph.D. degree in 1986, 1988 and 1944, respectively, from Seoul National University. From 1993 to 1994 he was engaged as a research engineer at Korea Telecom. Since 1995, he has been a professor at Chonam National University. His current research topics are audio-visual speech process, image processing and cognitive radio.

Seung You Na received the B.S. degree in electronics engineering from the Seoul National University in 1977, M.S. and Ph.D. degree from the University of Iowa in 1984 and 1986 respectively. He joined the department of electronics and computer engineering, Chonnam National University, South Korea in 1987. His research interests include signal processing, sensors, control and robotics.

Hyoung-Gook Kim received a Dipl.-Ing. degree in Electrical Engineering and a Dr.-Ing. degree in Computer Science from the Technical University of Berlin, Berlin, Germany. From 1998 to 2005, he worked on mobile service robots at Daimler Benz, speech recognition at Siemens, and speech signal processing at Cortologic, and he served as adjunct professor of the Communication Systems Department, Technical University of Berlin, Berlin, Germany. From 2005 to 2007, he was a project leader at the Samsung Advanced Institute of Technology, Korea. Since 2007, he has been a professor in the Department of Wireless Communications Engineering, Kwangwoon University, Korea. His research interests include audio signal processing, audio-visual content indexing and retrieval, speech enhancement, and robust speech recognition.

Seung-Ho Choi received Ph.D. in Department of Electronics Engineering, Myungji University in 1992. From 1992 he has been a professor in Department of Computer Science, Dongshin University. His research interests are speech and image processing.