Correlation-Index Blind Classification for MFSK with Unreconstructed Compressive Samplings

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Abstract —To improve the speed of traditional signal sampling and processing, which is based on the Nyqusit-sampling theorem, a new theorem called Compressive Sensing (CS) is presented. Most work in CS has focused on reconstructing the high-bandwidth signals from nonuniform low-rate samples. However, the signal reconstruction process of CS needs large amount of computation. In this paper, under the frame of CS, a method called Correlation-Index Blind Classification (CIBC) using the Correlation-Index to realize MFSK signal classification is presented, which exploits the compressive measurements without reconstructing the original signal or knowing any parameter. CIBC processes the compressive measurements directly, avoiding the high computation of reconstruction. What's more, compared with the traditional Peak-Index, the promotion of computing speed is significant, and the performance decreases very little. The simulation results show that CIBC has good performance and low computation complexity. It's an effective method to improve the real-time performance of communication system.

Index Terms—Compressive sensing, correlation-index, blind classification, MFSK signal

I. INTRODUCTION

As we know, signal sampling is the key approach from the analog world to the digital world. The Shannon-Nyquist theorem is the classical theorem for signal sampling, which specifies that the sampling rate must be at least twice of the signal's maximum frequency to avoid losing information. However, as bandwidth of signal becoming wider, the sampling rate becomes higher and the electron devices such as analog-to-digital converters cost more.

A new theorem called compressive sensing for simultaneous sensing and compression has developed recently. A potentially large reduction can be realized in the sampling and computation costs for a communication system under CS framework. Candès [1], Tao [2] and Donoho [3] present CS in 2006. CS specifies that a signal having a spare representation in one basis can be reconstructed from a small set of projections onto a second measurement basis that is incoherent with the first basis. From Ref. [4], random projections are a universal measurement basis in the sense that they are incoherent with any other fixed basis with high probability. The CS measurement process is nonadaptive; the reconstruction process is nonlinear. CS can be used to illustrate the links between data acquisition, compression, dimensionality reduction, and optimization in undergraduate and graduate digital signal processing, statistics, and applied mathematics courses. CS has many promising applications in signal acquisition, compression, radar, medical imaging, and sensor networks.

In the modern communication system, modulation classification is an important step between the signal receiving and the signal demodulation. Especially in the non-cooperative communication systems, modulation classification plays a more significant role which can identify the modulation type of a modulated signal corrupted by noise. Many methods have been used in the modulation classification, such as spectrum, moments, zero crossings and Bayes decision theory [5]-[16].

While the CS theory has focused almost exclusively on the problems of signal reconstruction or approximation, it is not necessary. For instance, in many signal processing applications (including most communications and many radar systems), signals are acquired only for the purpose of making a detection or classification decision. Our aim in this paper is to show that the CS framework is useful for a much wider range of statistical inference tasks. Tasks such as classification do not require the reconstruction of the signal, but only require estimation of the relevant and useful features for the problem. The key finding is that in many cases it is possible to directly extract the features from a small number of random projections without ever reconstructing the signal. Using compressive measurements directly expands on the previous work of signal classification.

Under the framework of CS, the first step is reconstructing the original signal, but the reconstruction processing has a high computation complexity. However, for classification, it's not necessary to get the complete original signal. Instead, some class features abstracted from compressive measurements are enough. The papers on the modulation classification under CS frame is not too many, including N^{th} power nonlinear features algorithm [17] and complete reconstruction algorithm [18]. The N^{th} power nonlinear features algorithm taking advantages of the nonuniform low-rate samples recognizes signal in the compressive domain, which

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reduces the amount of data, but it has bad performance under low signal-to-noise ratio. The complete reconstruction method has a good classification performance. However, on one hand, the reconstruction processing needs high computation complexity, on the other hand, the compressive measurements is recovered to the high dimension, losing the advantage of small amount of data.

The existing MFSK signal compressive classification and demodulation algorithm [19] is based the model of 1-sparse and 2-sparse of MFSK signal. The algorithm hold that each symbol of MFSK signal is 1-sparse and the symbol rate is known as a priori condition. However, as it uses the rectangular window as long as the symbol width to observe the signal, to achieve the 1-sparse model, very high sample rate is needed to reduce the impact of spectrum leaking. But too high sample rate causes the data is too large, algorithm of Ref. [19] has little practical significance. In the framework of CS, modulation classification called CIBC can process far less data than the conventional approach with the Nyquist sampling rate, so that the speed of modulation classification will be faster and the real-time performance of the communication system can be promoted significantly. What's more, Ref. [20] uses cyclic feature to realize modulation recognition.

The rest of the paper is organized as follows. In section II, an overview of Compressive Sensing (CS) is presented. The algorithm of modulation classification of MFSK in compressive domain is introduced in section III. Simulation results are presented in Section IV to show the effectiveness of the modulation classification algorithm based on compressive sensing. We finish with concluding remarks in Section V.

II. Compressive Sensing

A. Sparse Representation of Signal

If a few entries of a signal are zero or close to zero, this signal is sparse or compressible. Generally, a signal in time domain is always not sparse. However, in some other domains, the signal may be represented sparsely. Consider a finite-length, one-dimensional, discrete-time signal $\boldsymbol{x}$ which can be represented by a vector with elements $x[n]$ in $\boldsymbol{R}^N$, $n=1,2,...,N$. And a basis $\boldsymbol{\Psi}$ consists of vectors $\boldsymbol{\psi}_{\mathrm{i}}$ which has N entries , $i=1,2,...N$. So the signal $\boldsymbol{x}$ can be expressed in the basis $\boldsymbol{\Psi}$ as follows:

$$\boldsymbol{x}=\boldsymbol{\Psi s} \tag{1}$$

where α is the $N\times 1$ column vector of weighting coefficients $\boldsymbol{s}_i =<\boldsymbol{x},\boldsymbol{\psi}_i>$. $\boldsymbol{s}$ is the representation of signal $\boldsymbol{x}$ in basis $\boldsymbol{\Psi}$. If the weighting coefficients $\boldsymbol{s}$ has only K entries non-zero, the signal $\boldsymbol{x}$ is K -sparse in basis $\boldsymbol{\Psi}$.

The coherence between measurement matrix $\boldsymbol{\Phi}$ and the representation basis $\boldsymbol{\Psi}$ can be expressed as: $\upsilon(\boldsymbol{\Phi},\boldsymbol{\Psi})=\sqrt{n}\cdot\max_{1\le k,j\le n}\left|\langle\phi_k,\psi_j\rangle\right|$, which means the largest correlation between any two atoms of $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$. If two matrix contain correlated atoms, the coherence is limited to range: $\upsilon(\boldsymbol{\Phi},\boldsymbol{\Psi})\in\left[1,\sqrt{n}\right]$. So $\upsilon(\boldsymbol{\Phi},\boldsymbol{\Psi})$ is a significantly important parameter to compressive sensing.

B. Compressive Sensing

Consider a $1\times M$ measurement vector $\boldsymbol{y}$ with M entries $y[m]$, $m=1,2,...,M$. A $M\times N(M<<N)$ measurement matrix $\boldsymbol{\Phi}$ can be viewed as $[\phi_1,\phi_2,...,\phi_M]^T$, and ϕ_j, $j=1,2,...,M$ is a $1\times M$ vector. $y[j]$ is generated by the inner production of $\boldsymbol{x}$ and ϕ_j , so that $\boldsymbol{y}$ can be written as

$$\boldsymbol{y}=\boldsymbol{\Phi x}=\boldsymbol{\Phi\Psi s}=\boldsymbol{\Theta s} \tag{2}$$

where $\boldsymbol{\Theta}$ is a $M\times N$ sensing matrix that $\boldsymbol{\Theta}=\boldsymbol{\Phi\Psi}$. The compressive process can be shown in Fig. 1.

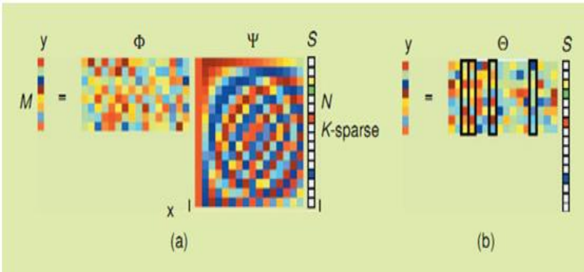

Fig. 1. Process of compressive sensing

Shown in Fig. 1(a), the vector of coefficients $\boldsymbol{s}$ is sparse with K = 4. In Fig. 1(b), there are four columns that correspond to nonzero $\boldsymbol{s}_i$ coefficients; the measurement vector $\boldsymbol{y}$ is a linear combination of these columns.

From Ref. [1], [2], the measurement process is non-adaptive, because the matrix $\boldsymbol{\Phi}$ is a fixed matrix which does not depend on signal $\boldsymbol{x}$. The sensing matrix needs satisfy RIP [21] , and each element of sensing matrix usually satisfies Gaussian or Bernoulli distribution.

C. The Restricted Isometry Property (RIP)

Candès [2] and Tao introduced the restricted isometry property (RIP) of a matrix and established its important role in CS. First define to be the set of all -sparse signals, i.e.

$$\sum\nolimits_K=\left\{\boldsymbol{x}\in R^N:\|\boldsymbol{x}\|_0:=|\mathrm{supp}(\boldsymbol{x})|\le K\right\} \tag{3}$$

where $\mathrm{supp}(\boldsymbol{x})\subset R^{\mathrm{N}}$ denotes the set of indices on which $\boldsymbol{x}$ is nonzero. We say that a matrix $\boldsymbol{\Phi}$ satisfies the RIP of order if there exists a constant $\delta\in(0,1)$, such that

$$(1-\delta)\|\boldsymbol{x}\|_2^2\le\|\boldsymbol{\Phi x}\|_2^2\le(1+\delta)\|\boldsymbol{x}\|_2^2 \tag{4}$$

holds for all $\boldsymbol{x} \in \sum_K$. In other words, if $\boldsymbol{\Phi}$ satisfies RIP, the distance between two signals will scarcely change when the signals are compacted onto a lower subspace. The RIP also ensures that any compressible signal can be successfully and accurately recovered from noisy measurements. If ϕ_{ij} (the coefficients of $\boldsymbol{\Phi}$) satisfies $\boldsymbol{N}(0, \frac{1}{M})$, the (4) will hold on with high probability. What's more, The Gaussian measurement matrix $\boldsymbol{\Phi}$ has two interesting and useful properties[22]:

(1). The matrix $\boldsymbol{\Phi}$ is incoherent with the basis $\boldsymbol{\Psi} = \boldsymbol{I}$ of delta spikes with high probability. More specifically, an $M \times N$ independent and identically distributed (iid) Gaussian matrix $\boldsymbol{\Theta} = \boldsymbol{\Phi I} = \boldsymbol{\Phi}$ can be shown to have the RIP with high probability if $M \geq cK \log(N/K)$, with c a small constant. Therefore, K-parse and compressible signals of length N can be recovered from only $M \geq cK \log(N/K) \ll N$ random Gaussian measurements.

(2) The matrix $\boldsymbol{\Phi}$ is universal in the sense that $\boldsymbol{\Theta} = \boldsymbol{\Phi \Psi}$ will be iid Gaussian and thus have the RIP with high probability regardless of the choice of orthonormal basis $\boldsymbol{\Psi}$.

D. *Signal Reconstruction*

If the matrix satisfies the RIP, reconstruction problem of sparse signal $\boldsymbol{x}$ can be built as:

$$\min_{\tilde{s} \in R^N} \|\tilde{\boldsymbol{x}}\|_{l_1} \quad s.t. \quad \boldsymbol{\Phi} \tilde{\boldsymbol{x}} = \boldsymbol{\Phi \Psi} \tilde{\boldsymbol{s}} = \boldsymbol{y} \tag{5}$$

The matching pursuit algorithm is always used. And we also transfer the l_0-norm problem to l_1-norm, which can be expressed as:

$$\min_{\tilde{s} \in \boldsymbol{R}^N} \|\tilde{x}\|_{l_1} \quad s.t. \quad \boldsymbol{\Phi} \tilde{\boldsymbol{x}} = \boldsymbol{\Phi \Psi} \tilde{\boldsymbol{s}} = \boldsymbol{y} \tag{6}$$

Then basis pursuit algorithm [21] is used to solve the Eq. (6). However, the two algorithms to reconstruct the original $\boldsymbol{x}$ need large amount of computation. So instead of reconstructing the signal, processing the compressive measurements $\boldsymbol{y}$ to recognize the MFSK signal can reduce the computation complexity and promote the real-time performance. The algorithm presented in this paper do not reconstruct the original MFSK signal, and uses the compressive measurements directly to recognize the MFSK signal, which constructs the recognition features taking advantages of the significant peaks of MFSK signal in the frequency domain.

III. Compressive MFSK Signal Classification

A. *MFSK Signal Feature in Frequency Domain*

The model of received digital modulation signal can be built as:

$$r(t) = x(t) + v(t) = \sqrt{E} \sum_{-\infty}^{+\infty} a_n g(t - nT_s) \exp[j(\omega_c t + \theta_c)] + v(t) \tag{7}$$

where $x(t)$ is complex envelope signal, $v(t)$ is the complex additive white Gaussian noise, E is the energy of each symbol, a_n is the sent symbol sequence, $g(t)$ is baseband symbol pulse waveform, T_s is symbol width, ω_c is the carrier angular frequency, θ_c is the carrier phase. MFSK signal can be expressed:

$$r(t) = \sqrt{E} \sum_{-\infty}^{+\infty} \exp(j(\omega_n + \omega_c) t) g(t - nT_s) \exp(j\theta_c) \tag{8}$$

where $\omega_n \in \{(2m - 1 - M) \cdot \Delta\omega \mid m = 1, 2, ..., M\}$, $\Delta\omega$ is frequency deviation.

Doing the operation of discrete Fourier transform (DFT) for 2FSK signal, 4FSK signal and 8FSK signal, each spectrum is shown in Fig. 1-Fig. 3, and the prominent peaks can be found whose number is as same as the modulation order of FSK signal. The distance of peaks is the ω_n in (8). Fig. 2 shows the spectrum of 2FSK signal has 2 prominent peaks; Fig. 3 shows the spectrum of 4FSK signal has 4 prominent peaks; Fig. 4 shows the spectrum of 8FSK signal has 8 prominent peaks. What's more, detecting the number of spectrum peaks is a very useful method in engineering project. However, there are some problems for us the use this features. On one hand, as the signal contains the modulation information, the spectrum of FSK signal is non-sparse, even if there is no noise existing. On the other hand, compared with 2FSK signal and 4FSK signal, the peaks' amplitude of 8FSK signal is not so prominent, and when the noise is large, we can even not find out the peaks.

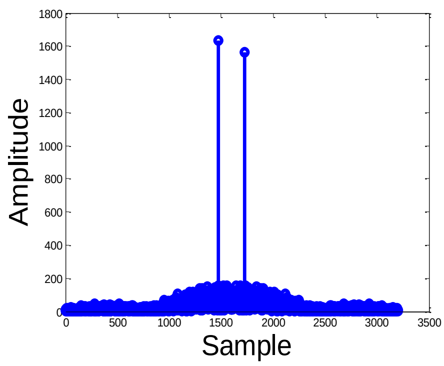

Fig. 2. The frequency spectrum of 2FSK

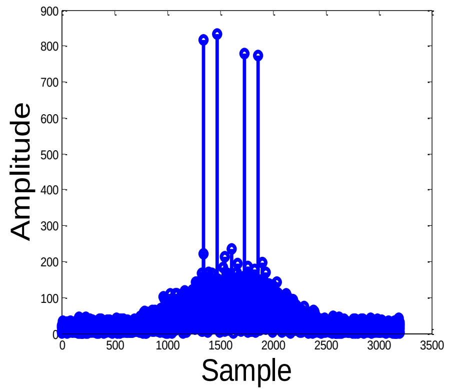

Fig. 3. The frequency spectrum of 4FSK

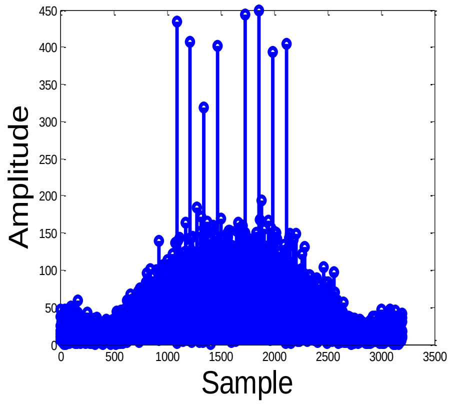

Fig. 4. The frequency spectrum of 8FSK

Ref. [23] define the Peak Index to class the MFSK signal. The first step of constructing the Peak-Index is calculate the absolute value of signal's frequency domain coefficients. Second, descend the absolute value and construct parameter A by summing the largest L values and construct parameter B by summing the $(L+1)$-th to $2L$-th values. Finally, define the L-Peak-Index C=A/B. Calculating the 2-Peak-Index, 4-Peak-Index and 8-Peak-Index of MFSK signal. The order of max Peak-Index above is as same as the order of modulation, i.e. the max Index of 4FSK signal is 4-Peak Index. Fig. 4-Fig. 6 is the simulation of Peak-Index under different signal-to noise ratio.

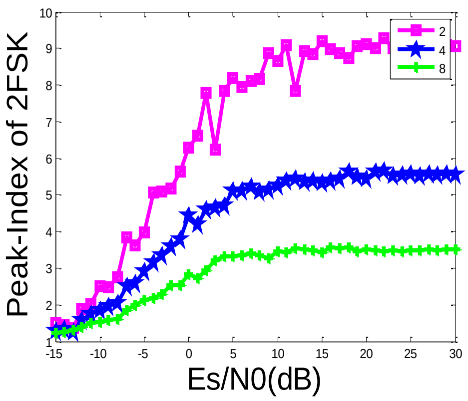

Fig. 5. Peak-Index of 2FSK

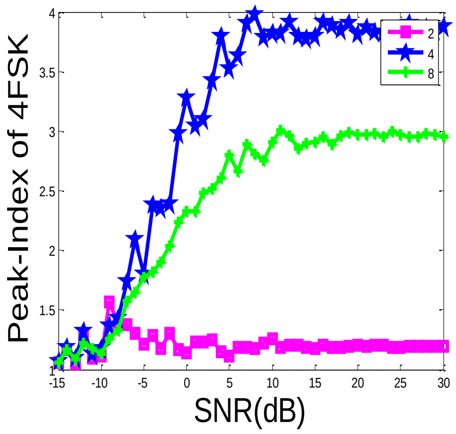

Fig. 6. Peak-Index of 4FSK

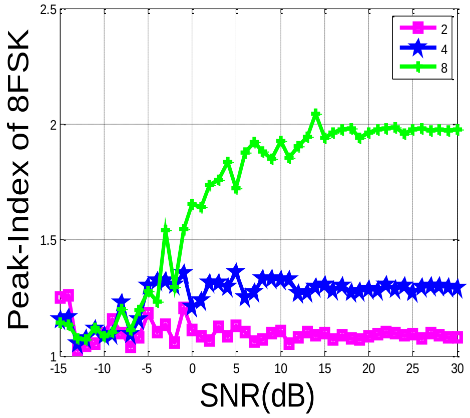

Fig. 7. Peak-Index of 8FSK

Fig. 5-Fig. 7 is the simulation of Peak-Index under different signal-to-noise ratio.

(1) 2FSK signal 2- Peak-Index is larger than 4- Peak - Index and 8- Peak - Index.
(2) 4FSK signal 4- Peak - Index is larger than 2- Peak - Index and 8- Peak - Index.
(3) 8FSK signal 8- Peak - Index is larger than 2- Peak - Index and 4- Peak - Index.

Compared with the Ref. [23], we can construct similar features in compressive domain to achieve the purpose of MFSK signal blind classification.

B. *Compressive MFSK Blind Classification*

Different from the traditional sampled signal, based on the CS frame, the sampled data is compressive measurements $\boldsymbol{y}=\boldsymbol{\Phi}(\boldsymbol{x}+\boldsymbol{v})$. Each elements of the compressive measurements is the weighted summation of original signal, which weighted by each coefficient of measurement matrix. So the features of original signal in frequency domain do not exist. However, though the original signal is compressed to a lower dimensional space, the Euclidean distance can nearly keep stable which is guaranteed by RIP. That means that compressive measurements has the distinction as well and we can distinguish the different signals in compressive space.

As the MSFK signal is not sparse in frequency domain, reconstruction is not accurate and the amount of calculation is large. Processing MFSK signal in compressive domain is a better choose. When important parameters, such as the order of FSK signal, the symbol rate and synchronization time are unknown, the algorithm presented in this paper constructs the Correlation-Index to class MFSK signal in compressive domain directly.

According to the CS, RIP guarantees that each K columns of sensing matrix is very close to orthogonal, the correlation is very little. So by calculating the inner product of compressive measurements vector and each sensing matrix's column, we can get the position of max amplitudes in sparse coefficients vector α , but we cannot get the accurate values. Although the accurate values is unknown, the inner product values can be used, which reflect the relationship of some largest non-zero amplitudes. Considering the MFSK signal is a nearly sparse signal, we use the inner product values to construct features and achieve MFSK signal blind recognition.

Calculating the inner product of compressive measurements $\boldsymbol{y}$ and sensing matrix $\boldsymbol{\Theta}$:

$$\boldsymbol{\mu} = \boldsymbol{\Theta}^H \boldsymbol{y} \tag{9}$$

where $\mu_i = <\boldsymbol{\Theta}_i^H, \boldsymbol{y}>$, $\boldsymbol{\Theta}_i$ is the i-th column, $i = 1, 2, ..., N$. The physical meaning of inner product is the degree of relation.

Descend $\boldsymbol{\mu}$, then get $\tilde{\boldsymbol{\mu}}$.

Define compressive L-Correlation-Index:

$$G_L = P_L / Q_L \tag{10}$$

where P_L is the summation of first L elements, and Q_L is the summation of the second L elements. The Correlation-Index G_L is used to be the MFSK signal recognition features. The process of constructing the Correlation-Index is shown as Fig. 8.

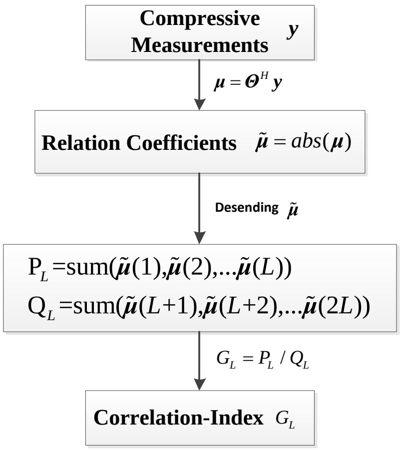

Fig. 8. The process of constructing the Correlation-Index

Fig. 9~11 are the FSK signal's Correlation-Index under different signal-to-noise ratio. As the Correlation-Index can reflect the spectral peak size in frequency domain, we can get the follow conclusion:

(1) 2FSK signal 2- Correlation- Index G_2 is larger than 4- Correlation- Index G_4 and 8- Correlation- Index G_8.

(2) 4FSK signal 4- Correlation- Index G_4 is larger than 2- Correlation- Index G_2 and 8- Correlation- Index G_8.

(3) 8FSK signal 8- Correlation- Index G_8 is larger than 2- Correlation- Index G_2 and 4- Correlation- Index G_4.

Based on the conclusion above, we can use the Correlation-Index to realize the blind classification of MFSK signal. When $G_2 > G_4 > G_8$, the decision output is 2FSK signal; when $G_4 > G_2 > G_8$, the decision output is 4FSK signal; when $G_8 > G_2 > G_4$, the decision output is 8FSK signal.

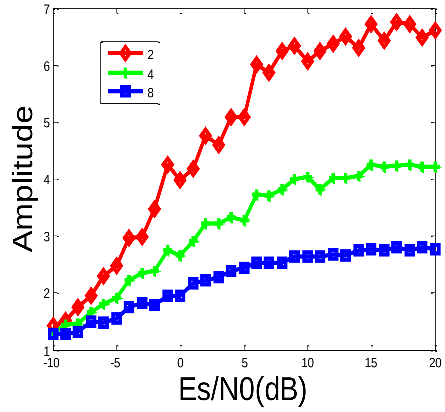

Fig. 9. Correlation-Index of 2FSK

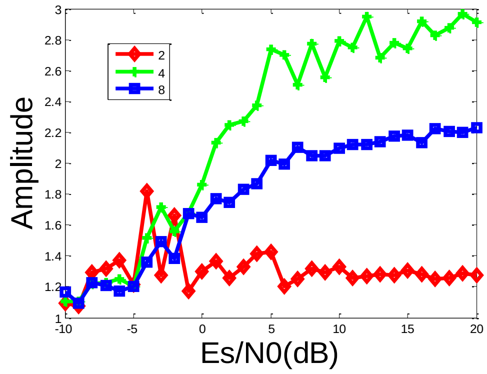

Fig. 10. Correlation-Index of 4FSK

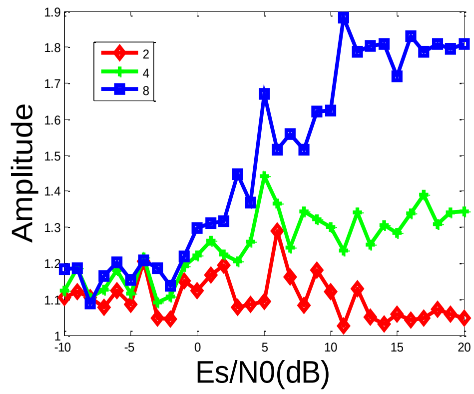

Fig. 11. Correlation-Index of 8FSK

IV. Simulation

For the set {2FSK, 4FSK, 8FSK},the simulation environment is: symbol rate 5MHz, sample rate 20MHz, symbol number 800, center frequency 10MHz, frequency deviation 0.8MHz. We define the signal-to noise ratio (SNR): $E_s / N_0 = 10\log_{10}(\frac{E_s}{N_0})$, where E_s is the energy of each symbol, and N_0 is the power spectral density of noise.

Shown as Fig. 12, when M/N=0.5, under the simulation enviroment above, the result is abtained. When E_s / N_0=-10dB, the correct probability of 2FSK is higher than 95%. When E_s/N_0 =-5dB, the correct probability of 4FSK is higher than 95%. When E_s/N_0=0dB, the correct probability of 8FSK is higher than 95%.

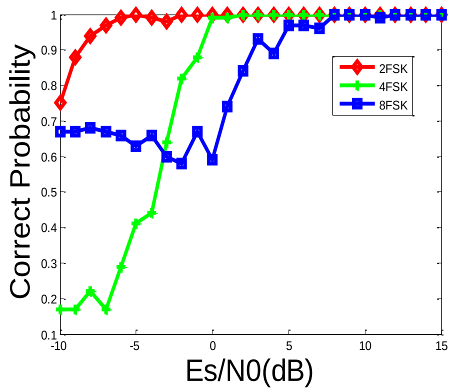

Fig. 12. performance of Correlation-Index algorithm

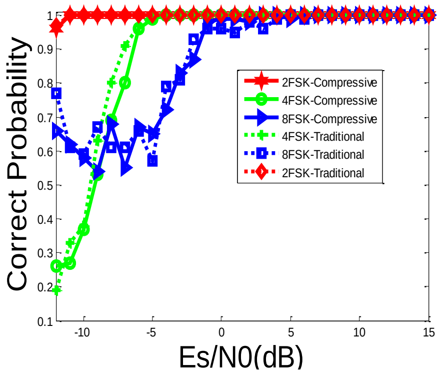

Fig. 13. Comparision of performance of Correlation-Index algorithm and Ref. [23]

The higher of SNR, the FSK signal's spectrum peak is more obvious. So the corresponding order of the Correlation-Index is larger, and the better of the blind classification performance. Under low SNR, the noise causes the peak we wanted is not significant, and more peaks is appeared. So from the result in Fig 12, the recognition prabobility of 8PSK is higher than 4PSK. Shown as Fig. 13, the performance of Ref. [23] is nearly as same as the algorthm's presented in this paper. The reason of performance loss is that the FSK signal is not completely sparse, and the Correlation-Index is not the real value of the FSK signal's spectrum peak. However, the computation complexity is reduced from $\mathcal{O}(N^2)$ to $\mathcal{O}(MN)$.

Shown as Fig. 14-16, under different SNR and compression ratio M/N, the M/N is larger, the performance of blind classification is better. For 4FSK with M/N=1/2, when E_s/N_0 =1dB, the correct probability is higher than 95%. And when M/N=1/4 or M/N=1/8, if the correct probability wants to achieve the same value, the E_s/N_0=4dB or 7dB.

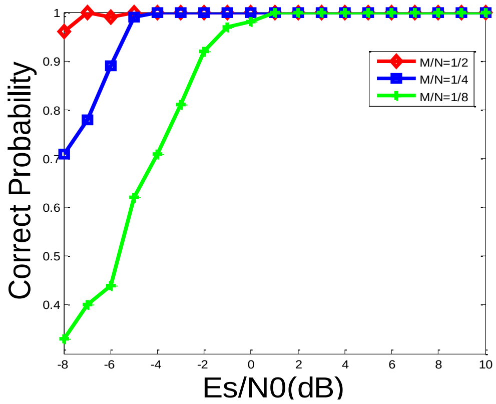

Fig. 14. Performance of 2FSK under different M/N

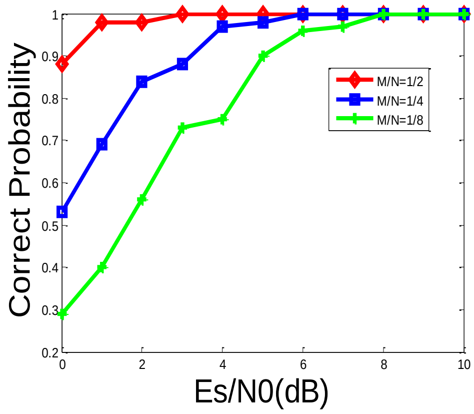

Fig. 15. Performance of 4FSK under different M/N

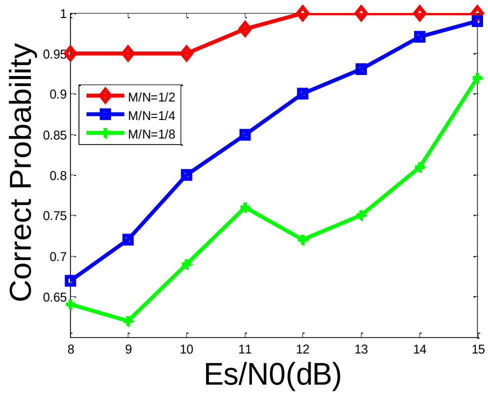

Fig. 16. Performance of 8FSK under different M/N

As noise is not sparse in frequency domian, it causes that when signal is compressed in low-dimension, the feature needed to be bastracted is harder and not very exact. The order of FSK signal is higher, the spectrum peak needed is more, which causes the impact of noise is greater, and the recognition performace is worse under low SNR.

Shown as Fig. 17-18, under different SNR and different symbol number, the symbol number is larger, the performance of blind classification is better. For 4FSK with 1000 symbols, when E_s/N_0=1dB, the correct probability is higher than 95%. And when the symbols is

800 or 600, if the correct probability wants to achieve the same value, the E_s / N_0=3dB or 5dB.

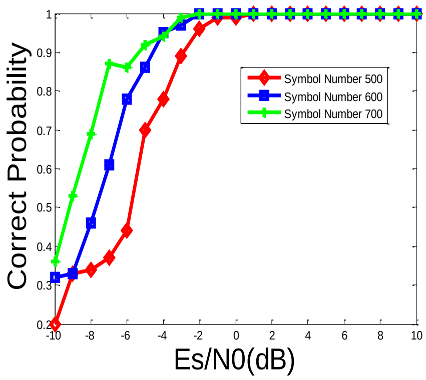

Fig. 17. Performance of 2FSK using different symbols

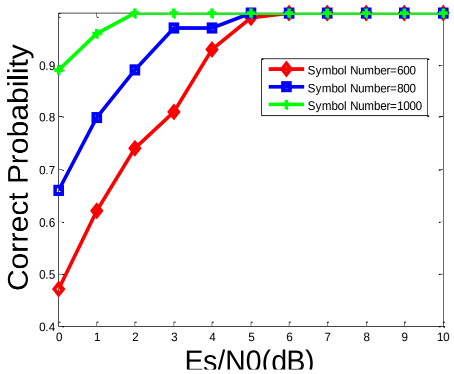

Fig. 18. Performance of 4FSK using different symbols

The more symbols is used to calculate the recognition feature, the more modulation information of FSK signal can be abstracted, so that the recognition performance is better.

V. Conclusions

The recently introduced theory of compressive sensing enables the reconstruction of sparse or compressible signals from a small set of nonadaptive, linear measurements. This has inspired the design of physical systems that directly implement similar measurement schemes. While most research has focused on the reconstruction of signals, many (if not most) signal processing problems do not require a full reconstruction of the signal. To significantly reduce the measurement burden compared to traditional Nyquist-rate automatic modulation recognition strategies, this paper presents an algorithm which achieves blind classification of MFSK signal in compressive domain directly. Simulation results confirm that automatic modulation recognition using sub-Nyquist Correlation-Index is indeed possible and viable, but compared to its Nyquist-rate Peak Index provided in Ref. [23], automatic modulation recognition using Correlation-Index requires somewhat higher SNR for a given probability of correct classification. Unknown any parameter and not to reconstruct the original signal, this algorithm processes the signal using compressive measurements directly to construct Correlation-Index G_L in compressive domain. Then the classification criterion is given. Simultaneously, simulation verify the theoretical derivation, and under low SNR, this algorithm has good performance. Unreconstructing the original signal, this algorithm can promote the real-time performance.

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