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Research Article

A Method Based on Random Demodulator and Waveform Matching Dictionary to Estimate LFM Signal Parameter

Shuo Meng,[1] **Chen Meng**,[1] **Cheng Wang**,[1] **and Xiang Yin**[2]

[1]*Shijiazhuang Campus, Army Engineering University of PLA, Shijiazhuang 050000, China*
[2]*32383 Troops, Beijing 010000, China*

Correspondence should be addressed to Chen Meng; 2895104899@qq.com

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The compressed sampling theory provides a good idea for sampling broadband linear frequency-modulated (LFM) signal, but the signal reconstruction after sampling should be considered when using the compressed sampling system to sample the signal. For the problem of estimating the parameters of the LFM signal under the condition of nonreconstruction, a method combining random demodulation (RD) and waveform matching (WM) dictionary is proposed in this paper. Firstly, the RD system is used to collect the compressed sampling data of LFM signal. In order to ensure the validity of the compressed sampling data, the value of the compressed sampling rate R in the RD system is discussed. Then, the feasibility of using compressed sampling data to estimate LFM signal parameters is theoretically demonstrated. According to the construction principle of waveform matching dictionary, the corresponding relationship between sparse representation coefficients, dictionary atoms, and signal parameters can be determined. Using this theory, the LFM signal parameters can be estimated. Finally, simulation and real signal experiments verify that the proposed method can realize the estimation of initial frequency and chirp rate of LFM signal when some prior information is known.

1. Introduction

Linear frequency-modulated (LFM) signal, also known as chirp signal, is widely used in electronic reconnaissance because of its unique anti-interference performance and strong survival performance in complex electromagnetic environment [1–3]. At the same time, with its advantages of high resolution, large bandwidth, and anti-Doppler frequency shift, it is also widely used in communications, medicine, and other livelihood fields. Through the analysis of intercepted enemy LFM signals in the battlefield environment, the intelligence information of the enemy can be obtained, which plays a key role in the victory or defeat of the war [4]. Therefore, the estimation of frequency parameters including initial frequency and frequency modulation (FM) slope has become one of the focuses of LFM signal research. However, with the development of information technology, the signal bandwidth continues to increase. Sampling methods based on Nyquist theorem will produce a large amount of data when processing LFM signals. This puts more pressure on the ADC at the sampling end, which poses more challenges to the development of hardware [5–7].

The development of analog information conversion technology based on compressed sensing has broadened the way of solving the problem of broadband signal acquisition [8, 9]. Existing simulation information conversion systems with relatively mature development include nonuniform sampling (NUS) [10–12], random demodulator (RD) [13–17] system, modulated wideband converter (MWC) [18–20], multicoset sampling [21], Nyquist folding receiver (NYFR) [22], and finite rate of innovation (FRI) [23]. However, the research on the compressed sampling technology has focused on the compressed sampling and reconstruction technology of the signal from the beginning, lacking the research on estimating the signal parameters directly using the compressed sampling information without reconstructing the original signal. In 2010, Davenport et al. [24] proved that it was feasible to directly use compressed sampling data to estimate signal parameters without reconstruction of the original signal, which promoted the rapid development of the research on compressed sampling parameter estimation. In reference [12], NUS system is used to compress and sample LFM signals, and matching pursuit algorithm is used to realize the estimation of LFM signal frequency parameters under nonuniform sampling. However, the random nonuniform triggering method adopted by the circuit will lead to Nyquist sampling interval between local adjacent sampling points, which cannot reduce the actual working bandwidth. Literatures [19, 20] combined MWC system with array structure and combined different reconstruction algorithms to estimate the direction of arrival (DOA) and carrier frequency of array signals. However, the multichannel structure of MWC system is more suitable for processing multiband signals, and the complex system structure increases the difficulty of hardware implementation. In reference [22], the structure of NYFR was improved by sinusoidal frequency modulation of local oscillator, which achieved good results for parameter estimation of frequency shift keying radar signal, but it was not suitable for the broadband characteristics of LFM signal. Although the FRI method proposed in literature [25] can directly estimate the signal parameter information with compressed sampled data, the structure design of FRI determines that the system is only limited to the pulse signal range.

Compared with the above methods, RD system is simple in structure, easy to implement, and widely used. Zhang et al. [15] combined RD system with array structure for parameter estimation of array signals, but special array structure is more suitable for processing multiband signals. Karampoulas et al. [17] proposed a dual channel sampling structure combining undersampling and RD system, which estimates the central frequency of the signal by recovering the position of the set to which the sparse vector belongs. However, this method is only effective for single-component LFM signals, and the dual channel structure design increases the complexity of the system and the difficulty of hardware implementation. In view of the above problems, literature [13] proposed to use the NUS system to compress the sampled signal and combine with the waveform matching dictionary to estimate the signal parameters. The construction of the waveform matching dictionary is a waveform matching method proposed by reference [26], which can intuitively reflect the difference between the reconstructed waveform and the original waveform, so as to facilitate the parameter estimation of the signal. Moreover, the method of waveform matching dictionary is intuitive and easy to construct and has strong adaptability to both single-component and multicomponent LFM signals.

However, the sampling of NUS does not get rid of the influence of Nyquist theorem. Therefore, this paper proposes a parameter estimation method combining RD compression sampling with waveform matching dictionary, which is mainly used to solve two problems: ne is to realize the compression sampling of LFM signals in RD systems, and the other is to estimate the parameter information of single-component and multicomponent LFM signals by combining WM dictionary and compressed sampling data.

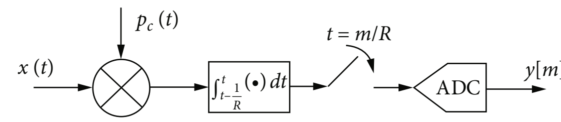


Figure 1: RD.

Table 1: Parameters of simulation signal.

Parameter	Signal a	Signal b
K	1	4
A_i	1	1
f_i (MHz)	200	[200 250 300 350]
k (MHz)	-300	-300
T (us)	1	1

2. Fundamental Theory

2.1. RD System. RD system is a kind of simulation information conversion technology based on compressed sensing theory. Due to its simple structure and easy hardware implementation, scholars at home and abroad have carried out extensive research on it, and it has been widely used in radar, communication, and other fields. The basic model of RD system is shown in Figure 1.

It can be seen from Figure 1 that RD system is mainly composed of mixer, integrator, and collector circuit structure. The input signal $x(t)$ is multiplied by $p_c(t)$ for frequency mixing modulation, and then, the modulated signal is low-pass filtered by the integrator. Finally, the collector samples at 1/R cycle and discretizes to obtain the compressed sampling observation sequence $y[m]$.

$p_c(t)$ is a pseudorandom sequence switched between ±1 with Nyquist frequency, and the expression is as follows:

$$p_c(t) = \varepsilon_n, t \in \left[\frac{n-1}{W}, \frac{n}{W}\right), n = 1, 2, \cdots, W, \quad (1)$$

where W is Nyquist sampling frequency and ε_n is ±1.

2.2. Mathematical Description of RD System

(1) *Signal mixing*. Mixed signals $x(t)$ and $p_c(t)$

$$y_1(t) = x(t)p_c(t). \quad (2)$$

Fourier transform of signal $y_1(t)$

$$Y(f) = \int_{-\infty}^{+\infty} y_1(t)e^{-j2\pi ft}dt = \int_{-\infty}^{+\infty} x(t)p(t)e^{-j2\pi ft}dt = X(f) * P(f), \quad (3)$$

where $X(f)$ is the spectrum of input signal $x(t)$, $P(f)$ is the spectrum of random sequence $p(t)$, and * is the convolution operation. As can be seen from Formula (3), the information of the signal after frequency mixing is distributed on the whole spectrum. Therefore, the low-frequency part obtained

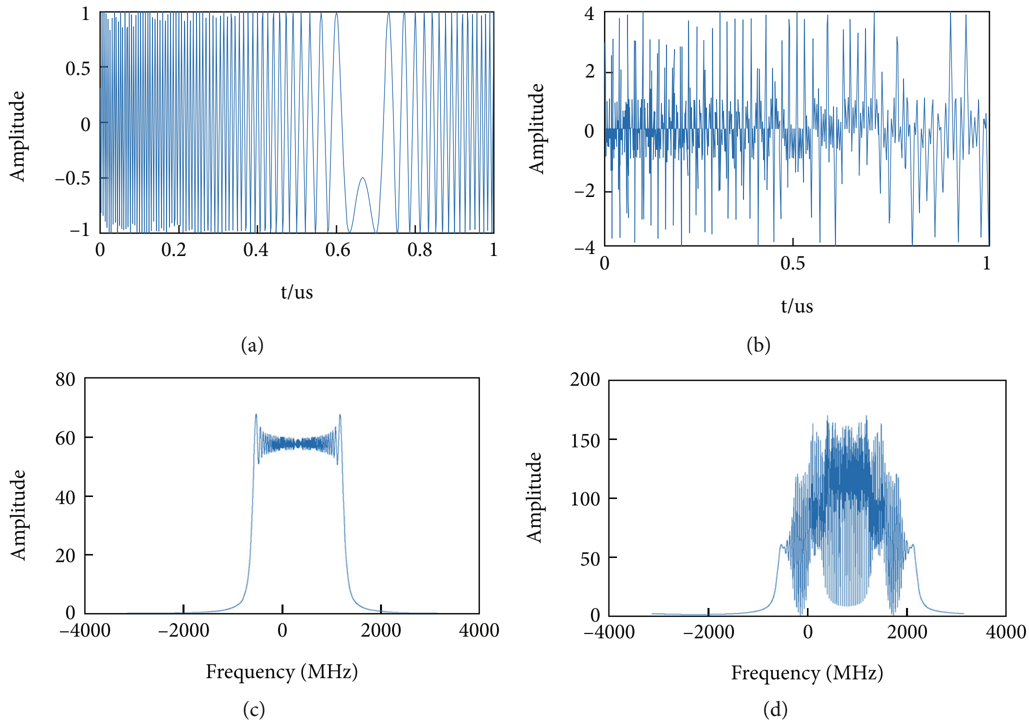


FIGURE 2: Simulation signal: (a) time domain, signal a; (b) time domain, signal b; (c) Fourier transform, signal a; (d) Fourier transform, signal b.

by low-pass filtering also contains all the information of the original signal.

(2) *Low pass filtering*. Perform low-pass filtering for $y_1(t)$, and the formula is as follows:

$$y_2(t) = (x(t) \cdot p(t)) * h(t) = \int_0^t x(\tau)p(\tau)h(t-\tau)d\tau, \quad (4)$$

where $h(t)$ is the functional expression of the impulse response of the low-pass filter.

(3) *Discrete sampling*. The filtered signal $y_2(t)$ is sampled by the collector:

$$y[m] = \int_0^t x(\tau)p(\tau) * h(t-\tau)d\tau \Big|_{t=m\Delta t} \quad \Delta t \geq 0, \quad (5)$$

where m is the number of samples, Δt is the reciprocal of the sampling rate R, that is, the sampling interval.

According to the compressed sensing theory, the compressed sampling observation value of the input signal is measured by the observation matrix of the original signal, and the formula is as follows:

$$y = \Phi x. \quad (6)$$

In the RD system, the observation matrix A is obtained by multiplying the discrete matrices of $p(t)$ and $h(t)$, which can be expressed by the following formula:

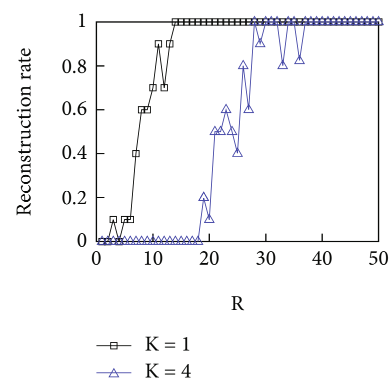


FIGURE 3: Reconstruction probability.

$$\Phi = HP, \quad (7)$$

$$H = \begin{bmatrix} h(C) & \cdots & h(1) & 0 & & \cdots \\ h(2C) & \cdots & \cdots & h(1) & 0 & \cdots \\ \vdots & & & \ddots & & \ddots \\ h(RC) & & & & h(1) & \end{bmatrix}_{R\times W}, \quad (8)$$

$$P = \begin{bmatrix} \varepsilon_0 & & & \\ & \ddots & & \\ & & \ddots & \\ & & & \varepsilon_{W-1} \end{bmatrix}_{W\times W}, \quad (9)$$

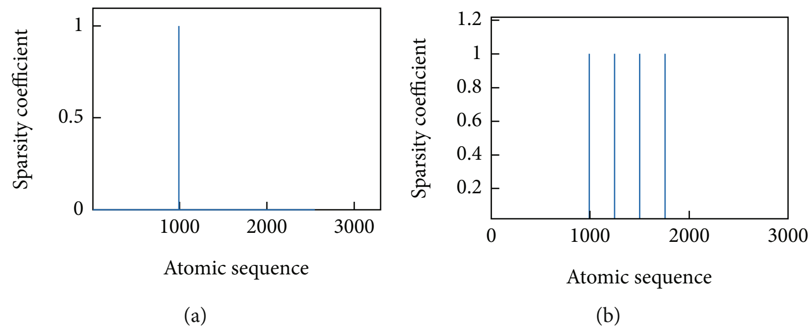


Figure 4: Sparse representation coefficient: (a) sparse representation, signal a; (b) sparse representation, signal b.

where P is a diagonal matrix of size $W \times W$, the size of H matrix is $R \times W$, and the ith row of H is the reverse order of $i \times C$ elements before filter impulse response $h(n)$. When the number of elements of $h(n)$ is less than $i \times C$, zero is added to the end of $h(n)$ before the reverse order, and then the reverse order and $C = W/R$.

After the signal measurement matrix is constructed, the process of signal $x(t)$ compression sampling can also be expressed as follows:

$$y = \Phi x = HPx. \tag{10}$$

3. Parameter Estimation Based on RD-Compressed Sampling

3.1. Constructing WM Dictionary. After obtaining the compressed sampling sequence of the signal, how to estimate the FM slope, initial frequency, and other parameters of the signal without reconstructing the original signal should also refer to the compressed sensing theory to design a sparse representation dictionary. The Fourier transform dictionary commonly used in traditional RD system is used to realize the sparse representation of signals. However, this method has poor sparsity and cannot directly use the observation sequence to estimate the parameters of signals. The WM dictionary not only has a good sparse representation performance for signals but also can realize the estimation of the FM slope and initial frequency of signals without reconstructing the original signals.

Suppose that the expression of multicomponent LFM signal is as follows:

$$x(t) = \sum_{i=1}^{K} A_i \exp\left[j2\pi\left(f_i t + \frac{1}{2}k_i t^2\right)\right], \tag{11}$$

where K is the number of LFM signal components, A_i and f_i are the amplitude and initial frequency of the ith component, respectively, and k_i is the FM slope.

When $K = 1$, the expression of single-component LFM signal is as follows:

$$x(t) = A \cdot \exp\left[j2\pi\left(f_c t + \frac{k}{2}t^2\right)\right]. \tag{12}$$

The atom of the WM dictionary is constructed according to Formula (12). The atom formula of the dictionary is as follows:

Table 2: The estimated parameters of simulation signal.

	Atomic sequence	$\hat{f}_i$ (MHz)	$\hat{k}$ (MHz/us)
Signal a	980	200	-300
Signal b	[980 1230 1480 1730]	[200 250 300 350]	-300

$$\Psi(t)_{p,q} = A \cdot \exp\left(j2\pi f_{cp} t + j\pi k_q t^2\right), \tag{13}$$

where f_{cp} and k_q are the initial frequency and FM slope of different parameters, respectively. On the premise that the ranges of f_c and k of signal $x(t)$ are known, the ranges of the two parameters are divided, respectively, and the ranges of the initial frequency are divided into P parts to obtain $f_{cp} = [f_{c1}, f_{c2}, \cdots f_{cP}]$, and the FM slope is divided into Q parts to obtain $k_{cq} = [k_1, k_2, \cdots k_Q]$.

Then, the WM dictionary is shown as follows:

$$\Psi = \left[\Psi_1, \cdots \Psi_{p,q}, \cdots, \Psi_Z\right]. \tag{14}$$

$Z = P \times Q$ indicates the number of atoms in the dictionary.

Then, the signal $x(t)$ can also be written in the form of linear combination of atoms in the WM dictionary:

$$x(t) = \sum_{i=1}^{i=Z} s_i \Psi_i(t). \tag{15}$$

Actually, Formula (15) is the expansion form of signal sparse representation formula $x = \Psi s$. By observing Equations (11) and (15), it can be seen that for the LFM signal composed of K components of the signal, there are K nonzero coefficients s_i in Formula (15), and the corresponding atomic sequence in the dictionary can be found by using s_i, and then, the estimated values of the initial frequency and FM slope of the original signal can be calculated by combining with Equation (13).

3.2. Parameter Estimation of Compressed Sampling. By determining the nonzero sparse representation coefficient s_i, the parameter estimation of the signal can be realized.

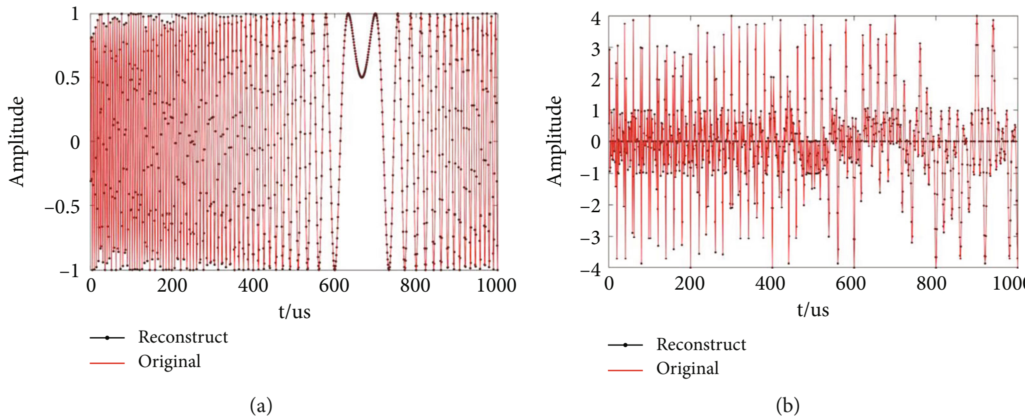


Figure 5: Original signal and reconstructed signal: (a) reconstruction, signal a; (b) reconstruction, signal b.

Table 3: Comparison for different methods.

Signal	Sampling	Sampling frequency (MHz)	Sampling points	Compression rate	Error
	Nyquist	1000	1000	1 : 1	/
Signal a	RD	40	40	25 : 1	1.124
	RD + WM	40	40	25 : 1	0
	Nyquist	1000	1000	1 : 1	/
Signal b	RD	40	40	25 : 1	1.097
	RD + WM	40	40	25 : 1	0

Then, the problem of signal parameter estimation can be transformed into solving the sparse representation coefficient of the signal under the condition that the observation value $y[m]$, the observation matrix Φ, and the sparse dictionary Ψ are known.

Assuming that the perception matrix Θ satisfies the finite isometric property, the reconstruction model of sparse representation coefficient can be expressed as

$$\hat{s} = \arg\min \|s\|_0, s.t. \Theta s = y, \tag{16}$$

where $y[m]$ is the observation sequence of RD system, $\Theta = \Phi\Psi$. The observation matrix Φ is obtained by Formula (7), and Ψ is the WM dictionary.

The sparse representation coefficients can be calculated by the reconstruction algorithm, and then, the atomic sequence can be determined, and the initial frequency and FM slope can be estimated.

In summary, the parameter estimation process of RD compression sampling and WM dictionary is summarized as follows:

Step 1: determine the value of the sampling rate R of RD system to ensure the effectiveness of compressed sampling data and obtain the observation sequence $y[m]$ by compressed sampling of $x(t)$

Step 2: construct a WM dictionary according to certain prior information and Formula (13) and obtain the relationship among sparse representation coefficients, atomic sequences, and parameters to be estimated according to the construction principle of the WM dictionary

Step 3: combined with reconstruction algorithm, the input is observation sequence $y[m]$, measurement matrix Φ, and WM dictionary Ψ, and the output is sparse representation coefficient

Step 4: according to Equations (13) and (15), the position of the maximum value in the sparse representation coefficient corresponds to the atom in the dictionary, and the initial slope and frequency modulation of the signal can be estimated by the determined atomic sequence

From the above parameter estimation steps, the parameter information of the original signal can be estimated by analyzing the compressed sampled data without reconstruction of the original signal.

4. Experimental Analysis

4.1. Simulation Signal. In order to verify the parameter estimation effect based on the compression sampling and WM dictionary of the RD system, the simulated LFM signal was experimentally analyzed. The simulation experiment environment is Windows 10 64-bit operating system and MATLAB R2018b software platform; the main parameters of the computer are processor Intel Core i7-10875H; the main frequency is 2.30GHz, and the memory is 16.0GB.

According to Formula (11), single-component and multicomponent LFM signals are, respectively, generated. The parameter settings of signal a and signal b are shown in Table 1. The time-domain waveform and spectrum of the obtained signal are shown in Figure 2. From the spectrum diagram of the signal, it can be seen that the signal does not have sparsity under Fourier transform.

4.2. Parameter Estimation of Simulation Signal. Different values of R will affect the compression sampling effect of

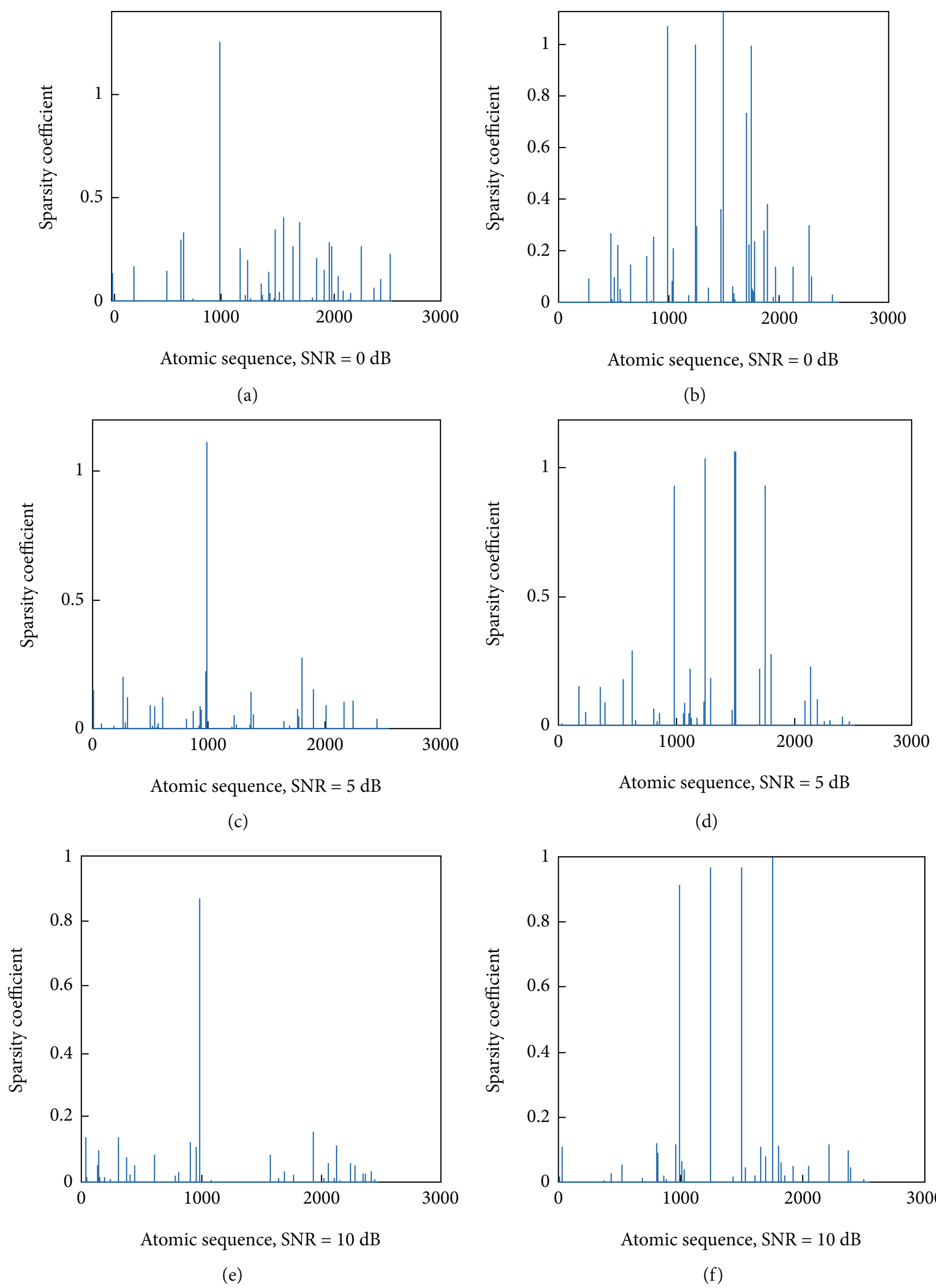


Figure 6: Sparse representation coefficient: (a) signal a, SNR = 0 dB; (b) signal b, SNR = 0 dB; (c) signal a, SNR = 5 dB; (d) signal b, SNR = 5 dB; (e) signal a, SNR = 10 dB; (f) signal b, SNR = 10 dB.

RD system. Therefore, the value of parameter R of RD system is determined first. The relative error (RE) of signal reconstruction is taken as the evaluation standard, and the formula is defined as follows:

$$E = \frac{\|\widehat{x}(t) - x(t)\|_2}{\|x(t)\|_2}, \tag{17}$$

where $\widehat{x}(t)$ is the reconstructed signal and $\|\cdot\|_2$ is L2 norm.

The reconstruction probability of signal a and signal b under different R values is analyzed. The matching pursuit algorithm is used as the recovery algorithm here, 500 Monte Carlo tests are carried out under each R value, and the corresponding relationship between R value and signal reconstruction probability is shown in Figure 3. When the relative error of signal reconstruction is less than 0.1, the signal reconstruction is considered successful, indicating that the compressed sampled data is effective.

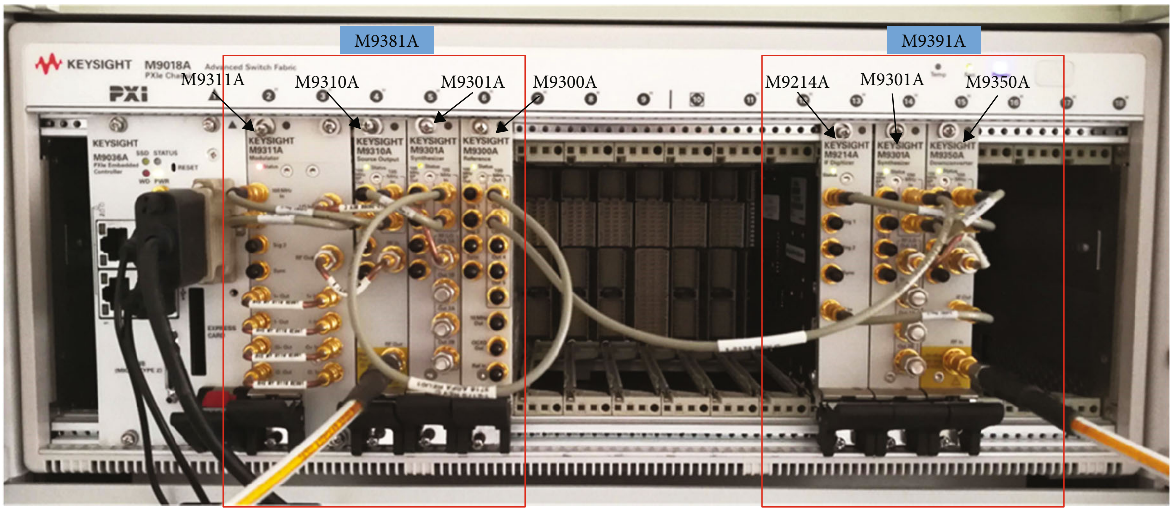


FIGURE 7: M9381A vector signal generator and M9391A vector signal analyzer.

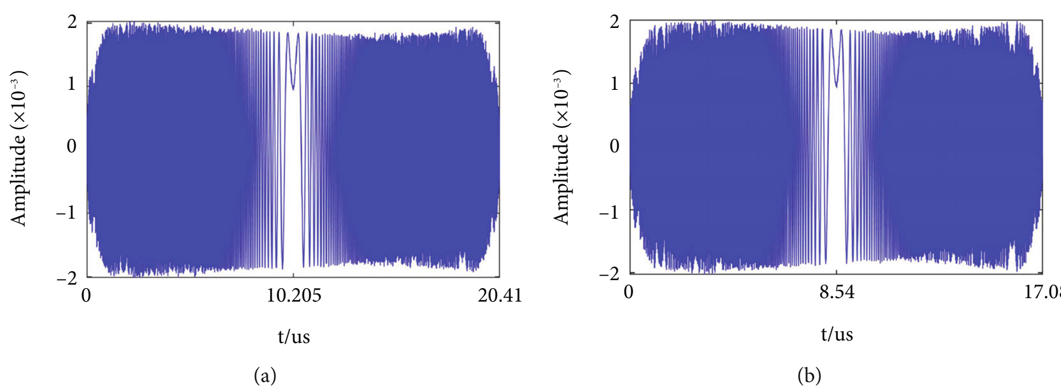


FIGURE 8: Measured signal: (a) waveform, signal c; (b) waveform, signal d.

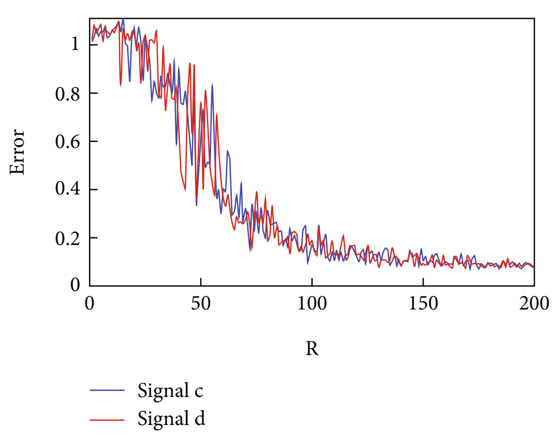


FIGURE 9: Reconstruction error.

Figure 3 discusses the two cases of signal a and signal b, respectively. It can be seen from the figure that when the value of R is greater than or equal to 40, the reconstruction effect of signal can be guaranteed for both cases. Therefore, the compression sampling rate of RD system is set to 40 for the subsequent compression sampling analysis of signal a and signal b.

After the value of R is determined, according to the parameters of LFM signal in Table 1, the ranges of initial frequency and FM slope are selected as (0 MHz, 500 MHz) and (-500 MHz/us, 0 MHz/us), respectively, and the two ranges are equally divided into 50 parts to obtain a redundant dictionary library with size of 50×50.

The sparse representation coefficients of the signal under the WM dictionary are recovered according to Formula (17). The matching pursuit algorithm is used as the recovery algorithm in the recovery process, and the sparse representation coefficients and corresponding atomic sequences of signal a and signal b are obtained as shown in Figure 4.

By comparing the Fourier transform of the signal in Figure 2, it can be seen that the WM dictionary has a better sparse representation effect. Meanwhile, the atomic sequence corresponding to the nonzero coefficient can be obtained from the figure, and then, the parameter estimates of signal a and signal b can be deduced according to Equations (13) and (14). The atomic sequence and parameter estimates corresponding to the nonzero coefficient are shown in Table 2. In order to reflect the parameter estimation effect of the proposed method more intuitively, the reconstructed signal can be obtained by using the obtained signal parameter estimation value and Formula (11). The

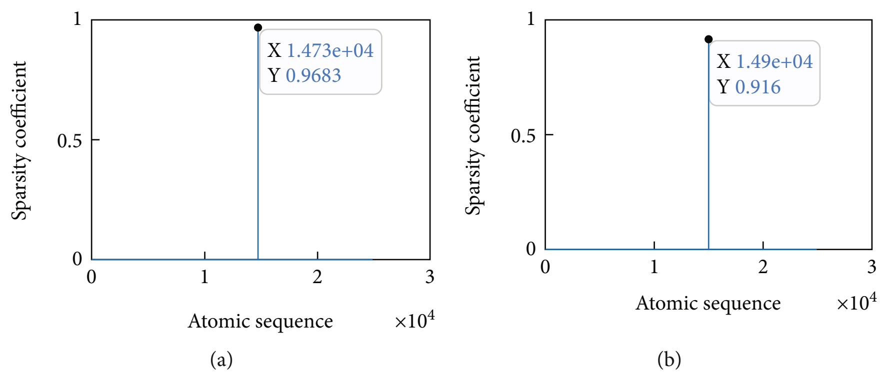


Figure 10: Sparse representation coefficient: (a) signal c; (b) signal d.

waveform of the reconstructed signal and the original signal is shown in Figure 5. The compression sampling effects of different sampling methods are compared, and the results are shown in Table 3.

According to the simulation analysis results in Tables 2 and 3 and Figure 5, it can be seen that compared with Nyquist sampling, the compression sampling frequency and sampling points of the RD system are reduced, and the initial frequency and FM slope of the signal can be effectively estimated by combining with the WM dictionary. Since the precision of signal parameter estimation is related to the precision of interval division during the construction of the WM dictionary, the interval selected here is exactly the same as the position precision of the atomic sequence corresponding to the sparse representation coefficient, so the parameter estimation value of the obtained signal is consistent with the original signal, and the waveform diagram of the reconstructed signal and the original signal in Figure 5 is also completely coincident.

4.3. Antinoise Performance Analysis. In the complex electronic reconnaissance environment, the detection signal is often doped with noise. In order to test the performance of the algorithm in noisy environment, Gaussian white noise with different signal-to-noise ratio is added to signal a and signal b, respectively. In the process of parameter estimation, WM dictionary and recovery algorithm are the same as those above. The sparse representation coefficients and atomic sequences of signals under different SNR conditions are obtained through analysis as shown in Figure 6.

In the simulation experiment, the conditions of 0 dB, 5 dB, and 10 dB are analyzed, respectively. It can be seen from the figure that the single-component signal is less affected by noise, and the position of the atomic sequence is more obvious, while the multicomponent signal is more affected by noise, and there will be some interference items close to the atomic sequence. For example, in Figure 6(b), the amplitude close to the sparse representation coefficient appears, which will cause misjudgment in the process of finding the corresponding atomic sequence, and then affects the result of parameter estimation. However, with the increase of SNR, the amplitude of the coefficient vector is more obvious, and the corresponding atomic sequence is easier to find. The above experiments show that the proposed method has certain antinoise performance, but when the SNR is lower than 0 dB, the interference term close to the sparse representation coefficient will be generated, which will affect the accuracy of parameter estimation.

By constructing the waveform matching dictionary, we can estimate the parameters of the LFM signal. The proposed method has a certain degree of antinoise ability and has better antinoise performance when analyzing the single-component LFM signal.

Table 4: The estimated parameters of measured signal.

	Atomic sequence	$\widehat{f}_i$ (MHz)	$\widehat{k}$ (MHz/us)
Signal c	14730	1300	4.90
Signal d	14900	1300	7.03

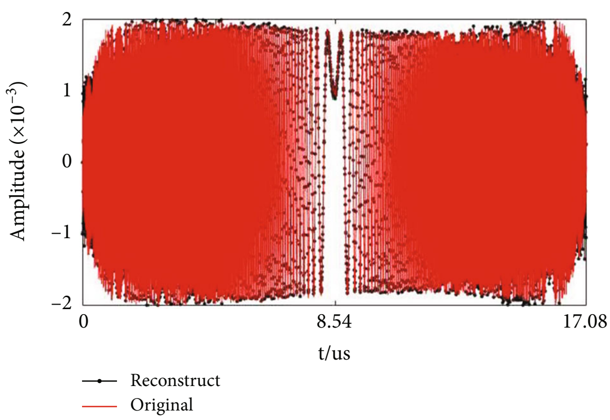
5. Measured Signal Analysis

LFM signals are generated and collected by M9381A vector signal generator and M9391A vector signal analyzer and other relevant experimental equipment. The M9381A vector signal generator mainly includes four modules: frequency synthesis module (M9301A), source output module (M9310A), digital vector modulation module (M9311A), and frequency reference module (M9300A). M9391A vector signal analyzer mainly includes intermediate frequency digital module (M9214A), frequency synthesis module (M9301A), and downconversion module (M9350A). The introduction of relevant experiments is mentioned in literature [27].

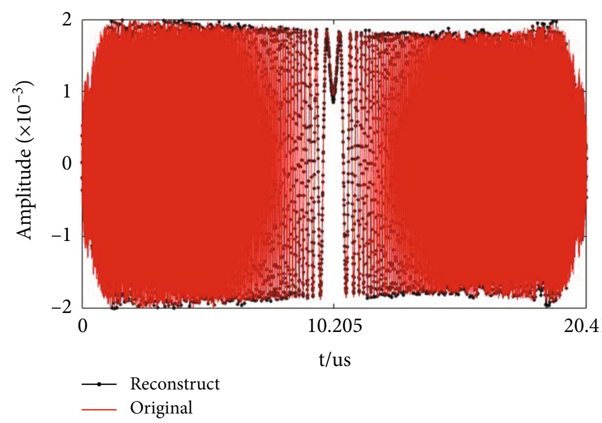
The output frequency range of M9381A vector signal generator is 1 MHz~6GHz, and the frequency resolution is 0.01 Hz. M9391A vector signal analyzer is connected to M9381A through wire connection to receive LFM signals. The operating frequency range of M9391A vector signal analyzer is 1 MHz~6GHz, and the frequency resolution is 0.001 Hz. The structure of the experimental equipment is shown in Figure 7. The simulation software was used to analyze the collected data to verify the effect of the waveform matching dictionary method on the parameter estimation of the measured signal under the condition of RD-compressed sampling.

Table 5: Comparison for sampling and analysis.

Signal	Sampling	Sampling frequency (MHz)	Sampling points	Compression rate	Error
Signal c	Nyquist	150	3061	1 : 1	/
	RD	8	163	18.75 : 1	1.332
	RD + WM	8	163	18.75 : 1	0.0031
Signal d	Nyquist	150	2562	1 : 1	/
	RD	10	171	15 : 1	1.328
	RD + WM	10	171	15 : 1	0.0043



(a)



(b)

Figure 11: Measured signal and reconstructed signal: (a) reconstruction, signal c; (b) reconstruction, signal d.

In the experiment, single-component LFM signals with bandwidth of 100 MHz and 120 MHz are, respectively, generated and collected, with amplitude of 2×10^{-3}, frequency of 1.3 GHz, and signal period of 20.41 μs and 17.08 μs. The generated LFM signal is represented by signal c and signal d, respectively, and the waveform diagram is shown in Figure 8.

Firstly, the sampling rate R is determined. Monte Carlo tests were conducted 500 times for each R value, and the corresponding relationship between R and relative error is obtained as shown in Figure 9. When the relative error is less than 0.1, R value is considered valid. According to the results in the figure, when R is greater than 150, the compression sampling effect can be guaranteed.

After the R value is determined, according to the parameter settings of the measured signal and the FM slope calculation formula $k = B/T$, the initial frequency and the FM slope interval are selected as (1100 MHz, 1600 MHz) and (3 MHz/us, 8 MHz/us), respectively, which are equally divided into 500 copies to obtain a redundant dictionary library with the size of 500×500. The sparse representation coefficient is reconstructed according to Formula (16) and the matching pursuit algorithm, and the amplitude is normalized to obtain the image of the atomic sequence as shown in Figure 10.

It can be seen from the figure that the WM dictionary still has a good sparse representation effect for the measured signal. The parameter estimates of signal c and signal d are calculated according to the atomic sequence, as shown in Table 4.

Set up the comparison experiment of different sampling methods, respectively, and use Nyquist sampling, traditional RD sampling, and the method RD + WM to carry out the comparative analysis of the measured signals. Formula (17) is still used as the judgment basis to compare the effects of the above three methods. The parameter setting of the sampling process and the reconstruction error of sampling are shown in Table 5. After the parameters to be estimated are obtained, the reconstructed signal is obtained according to Formula (11). The WM between the reconstructed signal and the original signal is shown in Figure 11.

As can be seen from Table 4, the estimated value of initial frequency is completely consistent with the measured signal, but the accuracy of the estimated value of FM slope only reaches two decimal places, because the accuracy of parameter estimation matches the accuracy of interval division in the construction process of WM dictionary.

It can be seen from Table 5 that the traditional Nyquist sampling method has a high sampling frequency, a large number of total sampling points, and a large amount of data to be processed, which will obviously bring some pressure to ADC. Although the traditional RD system also has the ability of compressing and sampling, it will produce large errors when processing LFM signals directly. In combination with the error results in Table 5 and the signal reconstruction waveform in Figure 11, although the precision division of the interval will have a certain impact on the parameter estimation results when constructing the WM dictionary, it can still achieve the parameter estimation of the signal with low error while ensuring the signal compression sampling effect.

6. Conclusion

A method based on the combination of RD system and WM dictionary is proposed, which can effectively solve the problem of LFM signal parameter estimation under the condition of incomplete reconstruction of the original signal. The main innovations are as follows: first, it solves the problem of LFM signal compression sampling. Compared with traditional Nyquist sampling, RD system can effectively reduce the sampling frequency and sampling points, thus relieving the pressure faced by ADC. Compared with other sampling systems, RD system also has the advantages of simple structure and easy hardware implementation. Second, a WM dictionary is constructed, and the relationship among sparse representation coefficients, dictionary atomic sequences, and parameters to be estimated is obtained through the construction principle of the WM dictionary. The feasibility of the method is demonstrated from the theoretical level. Third, the effectiveness of the proposed method is verified by combining simulation and measured signals. It can not only effectively reduce the amount of data compressed and sampled by LFM signals but also achieve parameter estimation of compressed and sampled LFM signals with low error, and it is also effective for multicomponent LFM signals.

This research provides a certain reference for solving the problem of LFM signal parameter estimation in the electronic reconnaissance environment, but the acquisition of prior information needs some empirical knowledge. Moreover, although the proposed method has a certain antinoise property, there is room for improvement for the interference of strong noise. Therefore, with the further development of the research, the exploration of LFM signal parameter estimation under complex conditions such as unknown prior information and strong noise can be considered and studied step by step.

Data Availability

The simulation data can be reproduced in the manuscript, and the measured data are measured in the laboratory. The data that support the findings of the study are available on request from the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

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References

[1] H. Zhang, T. Shan, S. Liu, and T. Ran, "Optimized sparse fractional Fourier transform: principle and performance analysis," *Signal Processing*, vol. 174, article 107646, 2020.

[2] S. Liu, Y. Ma, and S. Tao, "Segmented discrete polynomial-phase transform with coprime sampling," *The Journal of Engineering*, vol. 2019, no. 19, pp. 5619–5621, 2019.

[3] S. Liu, Y. D. Zhang, R. Tao, and F. Yuan, "A fast algorithm for multi-component LFM signal analysis exploiting segmented DPT and SDFrFT," in *IEEE International Radar Conference*, pp. 1139–1143, Arlington, VA, USA, 2015.

[4] R. Zhang, C. Meng, C. Wang, and Q. Wang, "A novel optimization method for bipolar chaotic Toeplitz measurement matrix in compressed sensing," *Journal of Sensors*, vol. 2021, Article ID 4024737, 11 pages, 2021.

[5] Z. Zhu, X. Zhou, Y. Du, Y. Feng, and X. Li, "A 14-bit 4-MS/s VCO-based SAR ADC with deep metastability facilitated mismatch calibration," *IEEE Journal of Solid-State Circuits*, vol. 6, no. 55, pp. 1565–1576, 2020.

[6] A. AlMarashli, J. Anders, J. Becker, and M. Ortmanns, "A Nyquist rate SAR ADC employing incremental sigma delta DAC achieving peak SFDR=107 dB at 80 kS/s," *IEEE Journal of Solid-State Circuits*, vol. 53, no. 5, pp. 1493–1507, 2017.

[7] B. Chen, F. Yaul, Z. Tan, and L. Fernando, "An adaptive SAR ADC for DC to Nyquist rate signals," in *2018 IEEE International Symposium on Circuits and Systems (ISCAS)*, pp. 1–5, Florence, Italy, 2018.

[8] Q. Wang, C. Meng, and C. Wang, "Analog-to-information conversion for nonstationary signals," *IEEE Access*, vol. 8, pp. 134067–134083, 2020.

[9] J. Šaliga, O. Kováč, and I. Andráš, "Analog-to-information conversion with random interval integration," *Sensors*, vol. 10, no. 21, pp. 35–43, 2021.

[10] Y. Gargouri, H. Petit, P. Loumeau, B. Cecconi, and P. Desgreysl, "Compressed sensing for astrophysical signals," in *2016 IEEE International Conference on Electronics, Circuits and Systems (ICECS)*, pp. 313–316, Monte Carlo, Monaco, 2016.

[11] M. Wakin, S. Becker, E. Nakamura et al., "A nonuniform sampler for wideband spectrally-sparse environments," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 2, no. 3, pp. 516–529, 2012.

[12] D. Gołowicz, P. Kasprzak, V. Orekhov, and K. Kazimierczuk, "Fast time-resolved NMR with non-uniform sampling," *Progress in Nuclear Magnetic Resonance Spectroscopy*, vol. 116, pp. 40–55, 2020.

[13] M. Polunin, A. Bykova, and V. V. Losev, "Analog to information converter with random demodulation based on SAR ADC," in *2021 IEEE conference of Russian young researchers in electrical and electronic engineering (ElConRus)*, pp. 2734–2738, St. Petersburg, Moscow, Russia, 2021.

[14] A. Harms, W. U. Bajwa, and R. Calderbank, "A constrained random demodulator for sub-Nyquist sampling," *IEEE Transactions on Signal Processing*, vol. 61, no. 3, pp. 707–723, 2013.

[15] J. Zhang, S. Yin, and W. Liu, "An FPGA implementation of orthogonal matching pursuit for random demodulation real-time reconstruction," in *2020 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*, pp. 1–6, Macau, China, 2020.

[16] A. Mm, B. Aih, and A. Hsm, "Sub-Nyquist wideband spectrum sensing based on analog to information converter for cognitive radio," *Procedia Computer Science*, vol. 182, pp. 132–139, 2021.

[17] D. Karampoulas, L. S. Dooley, and S. K. Mostefaoui, "Unified compressive sensing paradigm for the random demodulator and compressive multiplexer architectures," *IET Signal Processing*, vol. 14, no. 8, pp. 513–521, 2020.

[18] M. Mishali and Y. C. Eldar, “From theory to practice: sub-Nyquist sampling of sparse wideband analog signals,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, no. 4, pp. 375–391, 2010.

[19] Y. Guo, Z. Li, and J. Li, “Parameter estimation of frequency hopping signal based on MWC–MSBL reconstruction,” *IET Communications*, vol. 10, no. 14, pp. 1642–1649, 2020.

[20] Z. Byambadorj, K. Asami, T. J. Yamaguchi, A. Higo, M. Fujita, and T. Iizuka, “High-precision sub-Nyquist sampling system based on modulated wideband converter for communication device testing,” *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 69, no. 1, pp. 378–388, 2021.

[21] J. Dong, H. Li, Z. Fan, Q. Zhou, and S. Hua, “A joint optimization algorithm using adaptive minimum coset number based discrete multi-coset sampling,” *IEEE Access*, vol. 8, pp. 168659–168670, 2020.

[22] M. K. Haghighi, B. Zanj, and G. Baghersalimi, “Ultra-wideband channel estimation using multichannel sampling at the rate of innovation,” in *6th International Symposium on Telecommunications (IST)*, pp. 328–333, Tehran, Iran, 2013.

[23] Z. Qiu, P. Wang, and M. Sun, “Parameter estimation of frequency shift keying radar signal intercepted by Nyquist folding receiver using periodic linear frequency modulation local oscillator,” *IET Radar Sonar Navigation*, vol. 5, no. 15, pp. 1456–1470, 2021.

[24] M. A. Davenport, P. T. Boufounos, M. B. Wakin, and R. G. Baraniuk, “Signal processing with compressive measurements,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, no. 4, pp. 445–460, 2010.

[25] E. Baransky, G. Itzhak, N. Wagner, I. Shmuel, E. Shoshan, and Y. Eldar, “Sub-Nyquist radar prototype: hardware and algorithm,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 50, no. 2, pp. 809–822, 2014.

[26] F. K. Anjom, D. Teodor, C. Comina, R. Brossier, J. Virieux, and L. V. Socco, “Full-waveform matching of VP and VS models from surface waves,” *Geophysical Journal International*, vol. 218, no. 3, pp. 1873–1891, 2019.

[27] S. Meng, C. Meng, and C. Wang, *Parameter Estimation of LFM Signal Based on RD Compressed Sampling and DFRFT Dictionary*, 2022, https://www.researchsquare.com/article/rs-2174387/v1.