Wideband Signal Detection Based on MWC Discrete Compressed Sampling Structure

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Abstract: In order to solve the cross-channel signal problem caused by the uniform channelized wideband digital receiver when processing wideband signal and the problem that the sensitivity of the system greatly decreases when the bandwidth of wideband digital receiver increases, which both decrease the wideband radar signal detection performance, a new wideband digital receiver based on the modulated wideband converter (MWC) discrete compressed sampling structure and an energy detection method based on the new receiver are proposed. Firstly, the proposed receiver utilizes periodic pseudo-random sequences to mix wideband signals with baseband and other sub-bands. Then the mixed signals are low-pass filtered and downsampled to obtain the baseband compressed sampling data, which can increase the sensitivity of the system. Meanwhile, the cross-channel signal will all appear in any sub-bands, so the cross-channel signal problem can be solved easily by processing the baseband compressed sampling data. Secondly, we establish the signal detection model and formulate the criterion of the energy detection method. And we directly utilize the baseband compressed sampling data to carry out signal detection without signal reconstruction, which decreases the complexity of the algorithm and reduces the computational burden. Finally, simulation experiments demonstrate the effectiveness of the proposed receiver and show that the proposed signal detection method is effective in low signal-to-noise ratio (SNR) compared with the conventional energy detection and the probability of detection increases significantly when SNR increases.

Key words: wideband digital receiver; cross-channel signal; modulated wideband converter(MWC); compressed sampling; energy detection

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0 Introduction

Currently the electronic warfare environment becomes increasingly complex and constantly upgrades[1], so more and more radars apply low probability of intercept (LPI) signals, such as linear frequency modulated (LFM) signals which are anti-jamming and high-resolution[2] and frequency-agile signals whose carrier frequencies randomly hop[3] in order to increase their battlefield survivability and electronic countermeasure ability. At present, wideband digital receivers are commonly utilized to detect and acquire these wideband radar signals[4,5]. However, when the bandwidths of the received wideband radar signals reach the level of hundreds of MHz, the receiver sensitivity will greatly decrease. Besides, the widely applied uniform channelized wideband digital receiver will cause cross-channel signal problem[6] when processing wideband signals, which increases the difficulty of the subsequent processes such as signal detection, signal recognition[7], signal sorting[8] and so on. And only when we detect and acquire signal pulses, can we conduct the subsequent processes. At present, there are several conventional signal detection methods, including cyclostationary characteristic method, Wigner-Hough transform method and so on. Cyclostationary characteristic method requires that signals and noises utilize different cycle frequencies to ob-

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tain the excellent detection performance, and the amount of the computation is too much, which is not conducive to hardware implementation[9]. Wigner-Hough transform method is only confined to detect LFM signals[10], which is not suitable to be applied in the wideband digital receiver. Chen et al. proposed a detection method for the burst signals based on the cepstrum of the power spectrum, however, it is not suitable for detecting wideband signals[11]. Hanif et al. proposed a novel approach based on compressive sensing to detect Costas coded pulses, which can not be used to detect sparse multi-band signals[12]. Hariri et al. proposed a compressive detection method for sparse signals in additive white Gaussian noise without signal reconstruction, which has a high detection performance in low signal-to-noise ratio (SNR)[13].

In order to solve these problems which conventional wideband digital receiver faces, compressed sampling theory[14-16] gives us a new solution. A sub-Nyquist sampling method based on modulated wideband converter (MWC) was proposed[17-19], which works as a compressed sampling system that target continuous-time spectrally sparse signals. And Yang et al. improved MWC with run length limited sequences in the mixing operation to enlarge the input bandwidth of MWC[20]. Xu et al. proposed a distributed MWC schemes to reduce the hardware cost[21]. In this paper, we extend MWC to discrete-time domain in order to construct a new wideband digital receiver which could directly process signals sampled from analog-to-digital converter (ADC). The proposed receiver utilizes periodic pseudo-random sequences to mix the wideband radar signals with baseband and other sub-bands. For the baseband bandwidth is very small, a narrowband receiver can be utilized to receive the baseband signal which contains the full information of the original signals. And the whole design can increase the sensitivity of the receiver. Meanwhile, cross-channel signal will all appear in the baseband and any other sub-bands, we can solve the cross-channel signal problem easily just by processing the baseband. And we will directly process the compressed sampling data of the baseband without signal reconstruction, which greatly reduces the complexity and the amount of calculation.

Besides, in order to detect and acquire signal pulses, an energy detection method based on the proposed new wideband digital receiver is presented in this paper. In the case of the white Gaussian noise environment and absence of any prior knowledge, it is the optimal signal detection method[22-23]. Finally, a new energy detection model is designed and the detection criterion is established. The simulations show the effectiveness of the proposed receiver and demonstrate that the proposed energy detection method has a good signal detection performance.

1 New Wideband Digital Receiver

Fig. 1 shows the proposed new wideband digital receiver based on MWC discrete compressed sampling structure.

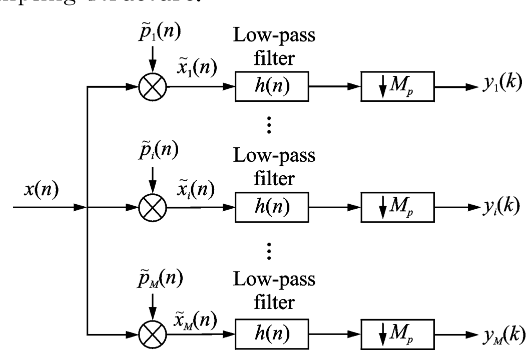

Fig. 1 Block diagram of the proposed new receiver

Let $x(n)$ be a complex-valued discrete-time signal with Nyquist sampling rate $f_{\mathrm{NYQ}} = 1/T$, where T denotes the sampling period. Therefore, $x(n)$ has a discrete-time Fourier transform (DTFT) and can be expressed as

$$x(n) = \frac{1}{2\pi}\int_{-\pi}^{\pi} X(\mathrm{e}^{\mathrm{j}\omega})\,\mathrm{e}^{\mathrm{j}n\omega}\,\mathrm{d}\omega \tag{1}$$

where $X(\mathrm{e}^{\mathrm{j}\omega}) = \sum_{n=-\infty}^{\infty} x(n)\mathrm{e}^{-\mathrm{j}n\omega}$ and $\omega = 2\pi fT$.

MWC consists of M parallel branches, where the received signals will be mixed with the periodic pseudo-random sequences firstly. $\widetilde{p}_i(n)$ ($1 \leqslant i \leqslant M$) is T_p -periodic pseudo-random sequence with $M_p = T_p f_{\mathrm{NYQ}}$ elements per period. Here $T_p = \frac{1}{f_p}$. Therefore, $\widetilde{p}_i(n)$ has a discrete Fourier expansion (DFS)

$$\widetilde{p}_i(n) = \frac{1}{M_p} \sum_{k=0}^{M_p-1} P_i(k) \mathrm{e}^{\mathrm{j}\frac{2\pi}{M_p} nk} \tag{2}$$

where $P_i(k)$ is the digital Fourier transform coefficients of the principal value sequence $p_i(n)$.

Then DTFT of the multiplication sequences $\widetilde{x}_i(n) = x(n)\widetilde{p}_i(n)$ is modeled as

$$\widetilde{x}_i(\mathrm{e}^{\mathrm{j}\omega}) = \sum_{n=-\infty}^{\infty} x(n) \cdot \widetilde{p}_i(n) \mathrm{e}^{-\mathrm{j}n\omega} = \sum_{n=-\infty}^{\infty} x(n) \cdot \frac{1}{M_p} \sum_{k=0}^{M_p-1} P_i(k) \mathrm{e}^{\mathrm{j}\frac{2\pi}{M_p} nk} \mathrm{e}^{-\mathrm{j}n\omega} = \frac{1}{M_p} \sum_{k=0}^{M_p-1} P_i(k) X\left(\omega - k\frac{2\pi}{M_p}\right) \tag{3}$$

The mixed signal $\widetilde{x}_i(n)$ is then low-pass filtered and downsampled at a low rate $f_s = 1/T_s = f_{\mathrm{NYQ}}/M_p$, where M_p is decimation factor. From Eq. (3), we can learn that the input of low-pass filter $H(f)$ is a linear combination of f_p -shifted copies of $X(f)$. Let us assume the low-pass filter $h(n)$ has a frequency response which is an ideal rectangular function, depicted as

$$H(\omega) = \mathrm{rect}\left(\frac{\omega f_{\mathrm{NYQ}}}{\pi f_s}\right) \tag{4}$$

Therefore, DTFT of the ith sequence $y_i(k)$ is expressed as

$$Y_i(\mathrm{e}^{\mathrm{j}\omega}) = \sum_{k=-\infty}^{\infty} y_i(k) \mathrm{e}^{-\mathrm{j}\omega n} = \sum_{l=-L_0}^{L_0} P'_i(l) X\left(\omega - l\frac{2\pi}{M_p}\right) \tag{5}$$

where $\omega = 2\pi f T_s$ and

$$P'_i(l) = \begin{cases} \frac{1}{M_p} P_i(l) & 0 \leqslant l \leqslant L_0 \\ \frac{1}{M_p} P_i(M_p + l) & -L_0 \leqslant l < 0 \end{cases} \tag{6}$$

where L_0 is chosen as the smallest integer such that the sum contains all nonzero contributions of over $X(\omega)$. The exact value of L_0 is calculated by $L_0 = \lfloor M_p/2 \rceil$, here $\lfloor \cdot \rceil$ denotes rounding the elements to the nearest integers.

Since the input signal $x(n)$ is a complex-valued discrete-time signal, we can obtain the compressed sensing matrix expressed as

$$\underbrace{\begin{bmatrix} Y_1(\mathrm{e}^{\mathrm{j}2\pi f T_s}) \\ Y_2(\mathrm{e}^{\mathrm{j}2\pi f T_s}) \\ \vdots \\ Y_M(\mathrm{e}^{\mathrm{j}2\pi f T_s}) \end{bmatrix}}_{\boldsymbol{y}(f)} = \frac{1}{M_p} \underbrace{\begin{bmatrix} p_{1,0} & \cdots & p_{1,M_p-1} \\ \vdots & \ddots & \vdots \\ p_{M,0} & \cdots & p_{M,M_p-1} \end{bmatrix}}_{\boldsymbol{P}} \cdot \underbrace{\begin{bmatrix} 1 & 1 & \cdots & 1 \\ 1 & \mathrm{e}^{\mathrm{j}\frac{2\pi}{M_p}} & \cdots & \mathrm{e}^{\mathrm{j}\frac{2\pi}{M_p}(M_p-1)} \\ 1 & \mathrm{e}^{\mathrm{j}\frac{2\pi}{M_p}(M_p-1)} & \cdots & \mathrm{e}^{\mathrm{j}\frac{2\pi}{M_p}(M_p-1)^2} \end{bmatrix}}_{\boldsymbol{F}} \cdot \underbrace{\begin{bmatrix} X(f) \\ \vdots \\ X(f + l \cdot f_p) \\ \vdots \\ X(f + (M_p - 1) \cdot f_p) \end{bmatrix}}_{\boldsymbol{z}(f)} \tag{7}$$

Considering all branches, it is convenient to rewrite Eq. (7) as

$$\boldsymbol{y}(f) = \boldsymbol{A}\boldsymbol{z}(f) \tag{8}$$

where $\boldsymbol{A} = \boldsymbol{PF}M_p$, denotes the compressed sampling matrix of size $M \times M_p$; $\boldsymbol{P}$ the $M \times M_p$ pseudo-random sequence matrix with $p_{i,j} \in \{+1, -1\}$; and $\boldsymbol{F}$ the $M_p \times M_p$ discrete Fourier transform matrix with $\boldsymbol{F}_j = [\theta^{0 \cdot j}, \theta^{1 \cdot j}, \cdots, \theta^{(M_p-1) \cdot j}]^{\mathrm{T}}$ ($0 \leqslant j \leqslant M_p - 1, \theta = \mathrm{e}^{\mathrm{j}\frac{2\pi}{M_p}}$), here $(\cdot)^{\mathrm{T}}$ denotes the transpose; $\boldsymbol{y}(f)$ is a column vector of length M with ith element

$$y_i(f) = Y_i(\mathrm{e}^{\mathrm{j}2\pi f T_s}) = \sum_{n=-\infty}^{\infty} y_i[n] \mathrm{e}^{-\mathrm{j}2\pi f n T_s} \tag{9}$$

The unknown vector $\boldsymbol{z}(f) = [z_0(f), z_1(f), \cdots, z_{M_p-1}(f)]^{\mathrm{T}}$ is of length M_p with $z_j(f) = X(f + \mathrm{j} f_p)$.

Fig. 2 shows the frequency spectrum of a cross-channel signal whose bandwidth is B and a mixing function. This spectrum of the received signal covers the frequency $nf_p/2$ ($n \in$ odd). Therefore, the spectrum on the right of the frequency $nf_p/2$ will be weighted by the right DFT coefficient near the signal spectrum and the left spectrum will be weighted by the left DFT coefficient according to Eq. (5), which will produce the mixed spectrums on the left and the right of each sub-band, respectively, as is shown in Fig. 3. All information of the cross-channel signal is contained in each sub-band. Therefore, whatever kinds of signals are processed, we can collect all the spectrum information from the compressed sampling data of the baseband or any other sub-bands without signal reconstruction.

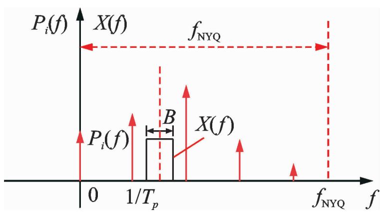

Fig. 2 Frequency spectrum of a cross-channel signal and a mixing function

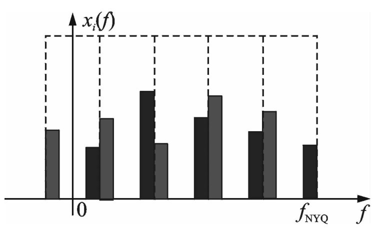

Fig. 3 Frequency information of MWC after mixing

2 Signal Detection Model

2.1 Conventional energy detection model

Conventional energy detection process is to calculate the energy statistics of the sampling sequence $y(n)$ sampled from the wideband ADC and then to compare the energy statistics with the calculated threshold to determine whether the signal exists or not.

Signal detection is a binary hypothesis testing process, the detection criterion can be expressed as follows

$$y(n)=\begin{cases}\eta(n) & H_0\\ s(n)+\eta(n) & H_1\end{cases} \tag{10}$$

where $s(n)$ is the useful signal, $\eta(n)$ the additive Gaussian white noise with zero mean and σ^2 variance, and $y(n)$ the sampling sequence. H_0 denotes that the useful signal $s(n)$ does not exist, while H_1 denotes that there is useful signal.

Based on Ref. [23], when there is no useful signal, the energy statistics distribution of the sampling sequence is

$$En=\frac{1}{N}\sum_{n=1}^{N}|\eta(n)|^2\sim \mathrm{Normal}\left(\sigma_\eta^2,\frac{2}{N}\sigma_\eta^4\right) \tag{11}$$

The threshold of the conventional energy detection is

$$\gamma=\sigma_\eta^2(N+\sqrt{2N}Q^{-1}(P_f)) \tag{12}$$

where P_f denotes the probability of false alarm and $Q(x)$ the standard normal distribution function.

2.2 The proposed energy detection model for one branch

Based on the above MWC discrete compressed sampling structure and principle, we propose a new energy detection method which is shown in Fig. 4.

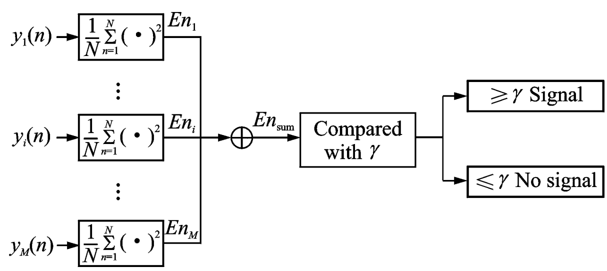

Fig. 4 Block diagram of energy detection based on MWC

After the compressed sampling by the proposed receiver, the binary hypothesis testing of the signal detection becomes to detect the compressed sampling sequence $y_i(n)$. According to Eq. (7), the detection model can be expressed as

$$y_i(n)=\begin{cases}\boldsymbol{A}_i\boldsymbol{\eta}_i(n) & H_0\\ \boldsymbol{A}_i(\boldsymbol{s}_i(n)+\boldsymbol{\eta}_i(n)) & H_1\end{cases} \tag{13}$$

where $y_i(n)$ is the compressed sampling sequence of the ith branch, $\boldsymbol{s}_i(n)=[s_0(n),s_1(n),\cdots,s_{M_p-1}(n)]^{\mathrm{T}}$ the useful signal vector of the ith branch and $\boldsymbol{s}_j(n)$ the useful signal sequence of the jth band in each branch of the new receiver (each branch has M_p sub-bands). $\boldsymbol{\eta}_i(n)=[\eta_0(n),\eta_1(n),\cdots,\eta_{M_p-1}(n)]^{\mathrm{T}}$ is the band-limited white noise vector where $\eta_j(n)$ $(0\leqslant j\leqslant M_p-1)$ is the Gaussian white noise sequence of the jth band in each branch, and $\boldsymbol{A}_i$ the ith row vector of the compressed sampling matrix $\boldsymbol{A}$.

The energy statistics of the compressed sampling sequence of the ith branch can be expressed as

$$En_i=\frac{1}{N}\sum_{n=1}^{N}|y_i(n)|^2 \tag{14}$$

Assuming that H_0 hypothesis is true, we randomly select one branch of MWC based on Eq. (7), expressed as

$$y_i(n)=\boldsymbol{A}_i\boldsymbol{\eta}_i(n)=\frac{1}{M_p}\boldsymbol{P}_i\boldsymbol{F}\boldsymbol{\eta}_i(n) \qquad (15)$$

where $\boldsymbol{P}_i$ denotes the ith row vector of periodic pseudo-random sequence matrix $\boldsymbol{P}$.

Thus Eq. (14) can be rewritten as

$$En_i=\frac{1}{N}\frac{1}{M_p^2}\boldsymbol{P}_i\boldsymbol{F}\left[\sum_{n=1}^{N}|\boldsymbol{\eta}_i(n)\boldsymbol{\eta}_i^{\mathrm{T}}(n)|\right]\boldsymbol{F}^{\mathrm{H}}\boldsymbol{P}_i^{\mathrm{T}} \qquad (16)$$

where $(\cdot)^{\mathrm{H}}$ denotes the conjugate transpose.

Defining $\boldsymbol{R}_\eta=\frac{1}{N}\sum_{n=1}^{N}|\boldsymbol{\eta}_i(n)\boldsymbol{\eta}_i^{\mathrm{T}}(n)|$, $\boldsymbol{R}_\eta$ can be expanded as the correlation matrix of band-limited white noise sequence $\boldsymbol{\eta}_j(n)$, where the diagonal elements are the autocorrelation of the white noise sequence and other elements are the cross correlation of the white noise sequence. Since the white Gaussian noise is modulated by the pseudo-random sequence and low-pass filtered, each sequence in the vector $\boldsymbol{\eta}_i(n)$ becomes uncorrelated band-limited white noise sequence. $\boldsymbol{R}_\eta$ can be further expressed as

$$\boldsymbol{R}_\eta=\mathrm{diag}\left[\frac{1}{N}\sum_{n=1}^{N}\eta_1^2(n),\frac{1}{N}\sum_{n=1}^{N}\eta_2^2(n),\cdots,\right.$$
$$\left.\frac{1}{N}\sum_{n=1}^{N}\eta_{M_p}^2(n)\right] \qquad (17)$$

Defining the autocorrelation of the white noise sequence as $R\triangleq\frac{1}{N}\sum_{n=1}^{N}\eta_j^2(n)$, then $\boldsymbol{R}_\eta$ can be written as

$$\boldsymbol{R}_\eta=R\boldsymbol{I} \qquad (18)$$

where $\boldsymbol{I}$ denotes $M_p\times M_p$ identity matrix.

According to Eq. (7), we know $\boldsymbol{F}\boldsymbol{F}^{\mathrm{H}}=M_p\boldsymbol{I}$, $\boldsymbol{P}_i\boldsymbol{P}_i^{\mathrm{T}}=M_p$, so Eq. (16) can be further expressed as

$$En_i=\frac{1}{M_p^2}\boldsymbol{P}_i\boldsymbol{F}R\boldsymbol{I}\boldsymbol{F}^{\mathrm{H}}\boldsymbol{P}_i^{\mathrm{T}}=\frac{1}{N}\sum_{n=1}^{N}\eta_j^2(n) \qquad (19)$$

Since the distribution of En_i the band-limited Gaussian white noise $\eta_j(n)$ is

$$\eta_j(n)\sim\mathrm{Normal}\left(0,\frac{\sigma_\eta^2}{M_p}\right) \qquad (20)$$

The distribution of En_i in the case of H_0 hypothesis can be expressed as

$$En_i=\frac{1}{N}\sum_{n=1}^{N}\eta_j^2(n)\sim\mathrm{Normal}\left(\frac{\sigma_\eta^2}{M_p},\frac{2\sigma_\eta^4}{NM_p^2}\right) \qquad (21)$$

In the practical detection, we can use a known probability of false alarm P_{f} to calculate each branch threshold γ_i. Since $P_{\mathrm{f}}=P(En_i>\gamma\mid H_0)$, we can obtain

$$Q\left(\frac{r_i-N\frac{\sigma_\eta^2}{M_p}}{\sqrt{2N\frac{\sigma_\eta^4}{M_p^2}}}\right)=P_{\mathrm{f}} \qquad (22)$$

where $Q(x)=\frac{1}{\sqrt{2\pi}}\int_x^{\infty}\exp\left(\frac{-x^2}{2}\right)\mathrm{d}x$ denotes complementary cumulative distribution function.

Finally, we can obtain each branch threshold γ_i expressed as

$$\gamma_i=\frac{\sigma_\eta^2}{M_p}(N+\sqrt{2N}Q^{-1}(P_{\mathrm{f}})) \qquad (23)$$

2.3 The proposed energy detection model for all branches

Assuming that the useful signal appear in the jth band of each branch of the proposed receiver when H_1 hypothesis is true, so at this time the useful signal vector is $\boldsymbol{s}_i(n)=[0,\cdots,s_j(n),\cdots,0]^{\mathrm{T}}$, and SNR of the original signal can be expressed as

$$\mathrm{SNR}=\left(\frac{1}{N}\sum_{n=1}^{N}s^2(n)\right)\Big/\left(\frac{1}{N}\sum_{n=1}^{N}\eta^2(n)\right)=$$
$$\left(\frac{1}{N}\sum_{n=1}^{N}s_j^2(n)\right)\Big/\left(\frac{1}{N}\sum_{n=1}^{N}\eta^2(n)\right) \qquad (24)$$

where $\frac{1}{N}\sum_{n=1}^{N}s^2(n)$ is the useful signal energy of the original signal, $\frac{1}{N}\sum_{n=1}^{N}\eta^2(n)$ the noise energy of the original signal, and $\frac{1}{N}\sum_{n=1}^{N}s_j^2(n)$ the useful signal energy of the jth band of each branch.

And the correlation matrix $\boldsymbol{R}_y$ of the compressed sampling signal can be expressed as

$$\boldsymbol{R}_y=\mathrm{diag}[R,\cdots,S+R,\cdots,R]=$$
$$\mathrm{diag}[0,\cdots,S,\cdots,0]+R\boldsymbol{I} \qquad (25)$$

where $S\triangleq\frac{1}{N}\sum_{n=1}^{N}s_j^2(n)$ denotes the autocorrelation of the jth band useful signal in each branch.

Similarly we can obtain the energy statistics of the ith branch compressed sampling sequence, depicted as

$$En_i=\frac{1}{M_p^2}\boldsymbol{P}_i\boldsymbol{F}R\boldsymbol{I}\boldsymbol{F}^{\mathrm{H}}\boldsymbol{P}_i^{\mathrm{T}}+\frac{1}{M_p^2}\boldsymbol{P}_i\boldsymbol{F}_jS\boldsymbol{F}_j^{\mathrm{H}}\boldsymbol{P}_i^{\mathrm{T}}=$$
$$R+\frac{1}{M_p}S=\frac{1}{N}\sum_{n=1}^{N}\eta_j^2(n)+\frac{1}{M_p}\frac{1}{N}\sum_{n=1}^{N}s_j^2(n) \qquad (26)$$

Therefore, SNR of the ith branch compressed sampling sequence is

$$\mathrm{SNR}=\left(\frac{1}{M_p}\frac{1}{N}\sum_{n=1}^{N}s_j^2(n)\right)\Bigg/\left(\frac{1}{N}\sum_{n=1}^{N}\eta_j^2(n)\right)=\left(\frac{1}{N}\sum_{n=1}^{N}s_j^2(n)\right)\Bigg/\left(M_p\frac{1}{N}\sum_{n=1}^{N}\eta_j^2(n)\right)=\left(\frac{1}{N}\sum_{n=1}^{N}s_j^2(n)\right)\Bigg/\left(\frac{1}{N}\sum_{n=1}^{N}\eta^2(n)\right) \tag{27}$$

Comparing Eq. (24) with Eq. (27), we learn that SNR of one branch compressed sampling sequence is equal to SNR of the original signal. If we only carry out one branch energy detection, it cannot reflect the superiority of multi-branch MWC discrete compressed sampling structure. Therefore, we can add the energies of all branches compressed sampling sequences together to carry out signal detection, expressed as

$$En_{\mathrm{sum}}=\sum_{i=1}^{M}En_i \tag{28}$$

The corresponding energy detection threshold can be expressed as

$$\gamma=\sum_{i=1}^{M}\gamma_i=\frac{M\sigma_\eta^2}{M_p}(N+\sqrt{2N}Q^{-1}(P_{\mathrm{f}})) \tag{29}$$

2.4 Pros and cons of the proposed method

As we know, with the electromagnetic environment which the electronic warfare faces becoming increasingly complex, conventional wideband digital receiver has met more and more challenges such as the large amount of sampling data to be processed, complex structure and cross-channel problem. Therefore, we propose a new wideband digital receiver based on the MWC discrete compressed sampling structure to solve these problems. The advantages of the proposed new receiver are described as follows:

(1) Realize sub-Nyquist sampling and save the storage space. Since the proposed new receiver is based on the compressed sampling, we can obtain the compressed sampling data at a sub-Nyquist sampling rate.

(2) Decrease the number of branch and reduce the complexity. The branch number of the proposed new receiver is related to the spectrally sparse level K of the radar signal. And the required branch number is $M\geqslant 2K$ for the complex signal model[17], which will reduce the complexities of the system and the hardware implementation.

(3) Solve cross-channel signal problem easily. Since the proposed new receiver utilizes pseudo-random sequences to mix signals to baseband, cross-channel signal will also appear in baseband. Therefore, we only need to process the baseband compressed sampling data to solve the cross-channel signal, whose complexity will decrease a lot compared with the conventional receiver.

However, the proposed new receiver needs M suitable pseudo-random sequences to complete the mixing operation, it is hard for us to choose the best periodic pseudo-random sequences which should be orthogonal with each other. And the compressed sampling data lose the true carrier frequency and phase difference information because of the mixing operation, it is a hard issue for us to estimate the true carrier frequency and direction of arrival (DOA) of the incident signal by directly processing the compressed sampling data.

Considering the energy detection method, we know that in the case of the white Gaussian noise environment and absence of any prior knowledge, it is the optimal signal detection method[22,23], which also has a low implementation complexity. However, when the signal is submerged in noise or interference, the conventional energy detection would be useless. Therefore, we propose to utilize all branches of compressed sampling data to carry out energy detection, which is proved to be able to increase the detection probabilities in low SNRs.

3 Numerical Simulations

In this section, several simulations are performed to verify the performance of the proposed energy detection method compared with the conventional energy detection. And we will detect wideband LFM signals and wideband frequency-agile signals in these simulations.

3.1 Wideband LFM signal detection

We detect wideband LFM signals by the proposed energy detection method for all branches compared with the conventional energy detection in different SNRs. Considering a wideband LFM signal which is parameterized by central frequency $f_0 = 1$ GHz, bandwidth $B = 800$ MHz and Nyquist sampling rate $f_{\mathrm{NYQ}} = 2.8$ GHz. The proposed new wideband digital receiver is parameterized as follows: The number of branches is set to $M = 20$, T_p -periodic pseudo random sequence is completed by Bernoulli random binary ± 1 sequence and the principal value sequence length $M_p = 50$, so $f_p = \frac{f_{\mathrm{NYQ}}}{50} = 56$ MHz. Here ideal low-pass filter is used and $f_s = f_p$ is designed. The white Gaussian noise is added and scaled so that the test signal has the desired SNR. Let the false alarm probability be $P_f = 0.01$. We calculate the threshold of conventional energy detection by Eq. (12) and the proposed energy detection threshold by the Eq. (29). One thousand Monte Carlo experiments are performed to count the probability of detection.

Fig. 5 shows the original wideband LFM signal pulse when SNR = 15 dB. Fig. 6 shows three branches of compressed sampling signal pulses randomly selected from the proposed new receiver when SNR = 15 dB. It can be seen from Fig. 6 that the three branches of pulses are different from the original signal pulse. If we only choose one branch of them to conduct energy detection, it cannot demonstrate the advantage of multi-branch MWC compressed sampling structure. Fig. 7 shows the cumulative compressed sampling signal pulse of all branches, we can obtain substantially the same signal pulse as the original signal pulse, which verifies the superiority of the proposed signal energy detection for all branches.

Fig. 8 shows the probability of detection of the proposed energy detection and the conventional energy detection for the wideband LFM signal. From the simulation results, we know that when SNR is above −5 dB, the proposed energy detection method and the conventional energy detection method both have a high detection performance

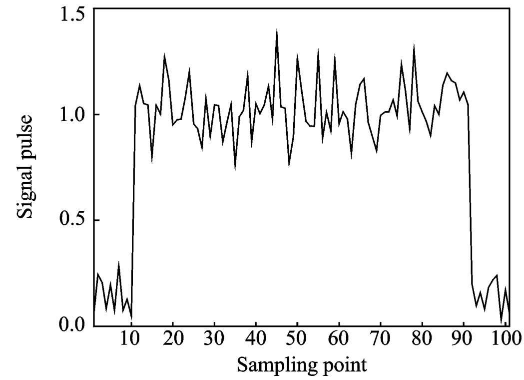

Fig. 5 Original signal pulse

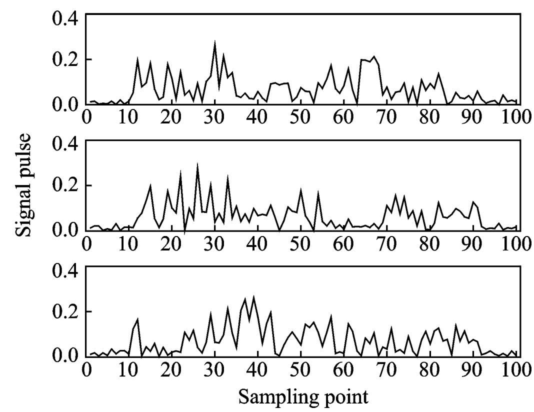

Fig. 6 Three branches of compressed sampling signal pulses

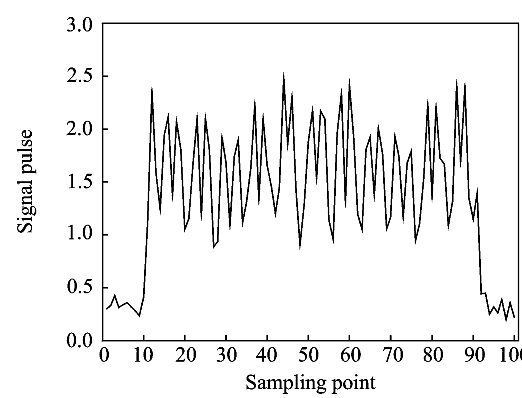

Fig. 7 Cumulative compressed sampling signal pulse of all branches

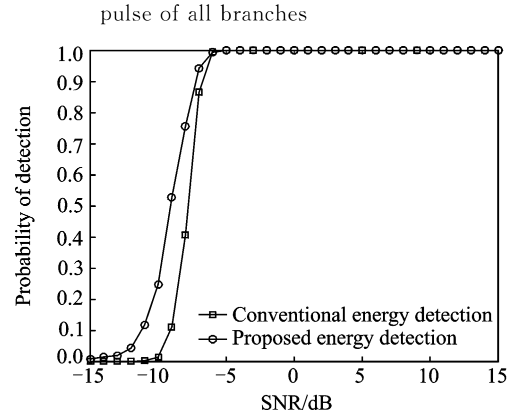

Fig. 8 Probability of detection for different SNRs of wideband LFM signal

and achieve 100% probability of detection. But when SNR is between −15 and −5 dB, the detection performance of the proposed energy detection is superior to the conventional energy detection, which verifies the effectiveness of the proposed method for detecting the wideband LFM signal.

The reason that we conduct signal detection is to obtain signal pulse. Only when we obtain signal pulse, can we further conduct signal recognition and other signal processing. Fig. 9 shows the original wideband LFM signal pulse without noise, the original signal pulse when SNR = −10 dB and the compressed sampling signal pulse when SNR = −10 dB. It is shown that when SNR = −10 dB, the original LFM signal has been completely submerged in noise and cannot be detected by the conventional energy detection. However, we can still obtain the signal pulse by the proposed energy detection method, which further demonstrate that proposed method is effective in low SNRs and that we can still utilize it to obtain signal pulse.

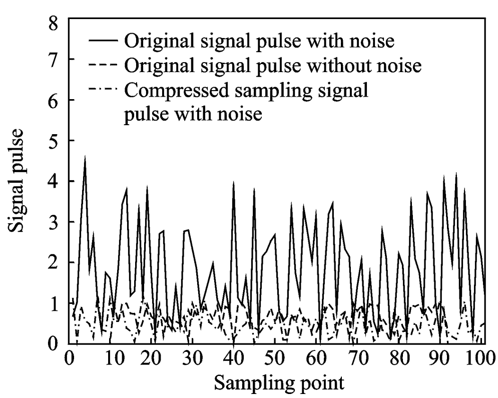

Fig. 9 Comparison of wideband LFM signal pulse for different methods

Fig. 10 shows the probability of detection for different branches $M=10,20,30$, and their corresponding final sub-Nyquist sampling rate are 560, 1 120 and 1 680 MHz which are much lower than the original Nyquist sampling rate. From Fig. 10, we can learn that the probability of detection increases when the number of the branch of the proposed new wideband digital receiver increases.

3.2 Frequency-agile signal detection

We carry out the same simulations as above

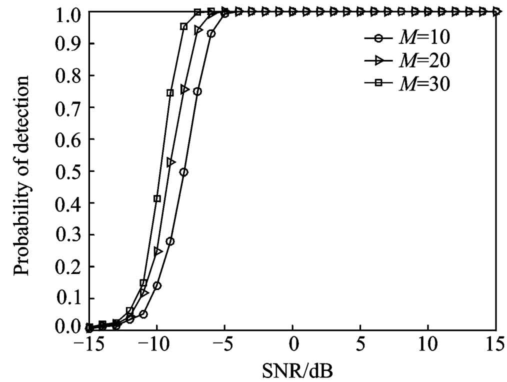

Fig. 10 Probability of detection for different branches of LFM signal

to detect wideband frequency-agile signals. Considering a wideband frequency-agile signal with ten randomly selected and different carrier frequencies, it is parametered by central frequency $f_0=600$ MHz, and Nyquist sampling rate $f_{\mathrm{NYQ}}=$ 2.8 GHz. The proposed new wideband digital receiver is parameterized as above. One thousand Monte Carlo experiments are performed to count the probability of detection.

Fig. 11 shows the probability of detection of the proposed signal energy detection and the conventional energy detection for the wideband frequency-agile signal. We can obtain the same results as the first simulation that when SNR is above −5 dB, the proposed energy detection method and the conventional energy detection method both have a high detection performance and can achieve 100% probability of detection. But when SNR is between −15 and −5 dB, the detection performance of the proposed signal energy detection is superior to the conventional energy detection, which verifies the proposed meth-

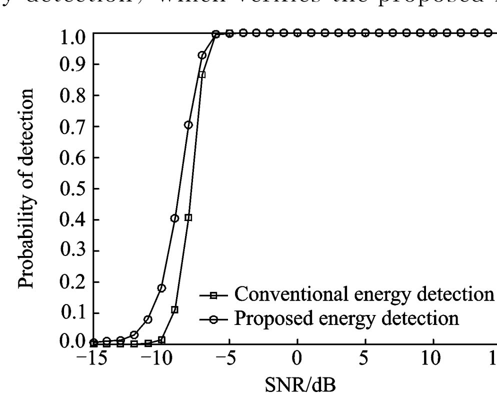

Fig. 11 Probability of detection for different SNRs of wideband frequency-agile signal

od is also effective for detecting wideband frequency-agile signals.

Fig. 12 shows the original wideband frequency-agile signal pulse without noise, the original signal pulse when SNR = −10 dB and the compressed sampling signal pulse when SNR = −10 dB. Similarly we can learn that when SNR = −10 dB, the original frequency-agile signal has been completely submerged in noise and cannot be detected by the conventional energy detection. However, we can still obtain signal pulse by the proposed energy detection method, which demonstrate the effectiveness and generality of the proposed signal detection method for acquiring different wideband signal pulses in low SNRs.

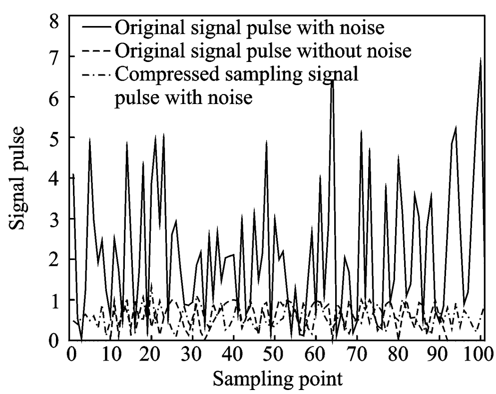

Fig. 12 Comparison of wideband frequency-agile signal pulse for different methods

Fig. 13 shows the probability of detection for different branches $M = 10, 20, 30$, and we can learn that the probability of detection increases when the number of the branch of the proposed new wideband digital receiver increases.

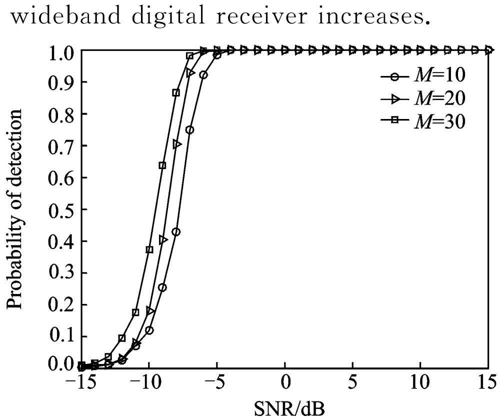

Fig. 13 Probability of detection for different branches of frequency-agile signal

4 Conclusions

Inspired by the conventional MWC compressed sampling structure, we propose a new wideband digital receiver based on the MWC discrete compressed sampling structure and utilize the energy detection method based on the proposed receiver to detect and acquire signal pulses. The proposed new receiver can increase the sensitivity and solve the cross-channel signal problem easily when detecting and processing wideband radar signals. Then we establish energy detection model and formulate the detection criterion based on the proposed receiver. And we directly utilize the compressed sampling data to carry out signal detection without signal reconstruction, which greatly reduces the complexity and decrease the calculation burden. The simulation results and some discussions are shown. These analyses and trials demonstrate the proposed receiver is effective and illustrate the proposed signal detection method can achieve better performances than the conventional energy detection in low SNRs. Besides, we can utilize the proposed method to detect and acquire the compressed sampling signal pulses which can be used to carry out signal recognition, such as carrier frequency and DOA estimation and so on. We will work on these aspects in the future.

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