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Interception Algorithm of S-cubed Signal Model in Stealth Radar Equipment

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Abstract

Radar equipment of stealth platforms such as aircraft have adopted the newest modern technology to design the signal waveforms. One of the important and effective methods is the hybrid waveform called spread spectrum stretch (S-cubed) which combines linear frequency modulation (LFM) and discrete phase code. In order to investigate the function of enemy's stealth radar equipment, the interception algorithm of S-cubed is needed. In this paper, a novel detection and parameter estimation approach for the reconnaissance S-cubed radar signal is presented. First, the generalized time-frequency representation of Zhao, Atlas, and Marks (ZAM-GTFR) and Hough transforms (HT) are applied to detecting the signal, and then the initial frequency and modulation slope of LFM are estimated from the ZAM-GTFR. On the basis of LFM information, the reconstructing signal is generated. Finally, the code rate of discrete phase code is extracted from the negative peaks of the ZAM-GTFR. Simulation results show that the proposed algorithm has higher estimation accuracy when the signal to noise ratio (SNR) is above 3 dB.

Keywords: signal detection; parameter estimation; spread spectrum stretch (S-cubed); generalized time-frequency representation (GTFR); Hough transforms

1. Introduction

In the past few decades, radio frequency (RF) radar stealth has become an important research focus, and one of the key problems is the waveform design for radar equipment of stealth platforms. Lynch [1] showed that a spread spectrum stretch (S-cubed) radar signal was often chosen as the waveform of stealth radar equipment. Since the instantaneous bandwidth of the S-cubed signal is wide, it is an effective waveform to fight against electronic support measures (ESMs) receiving equipment, making it difficult to complete the measurement of radar frequency and analysis of intra-pulse modulation.

The S-cubed signal is a kind of time-varying signal which could be analyzed by the time-frequency representation (TFR). A variety of TFR approaches have been presented for the detection and parameter estimation in some similar signals. Stankovi and Djurovi[2] applied the spectrogram and Wigner-Ville distribution (WVD) to motion parameter estimation. Kay and Boudreaux-Bartels [3] used WVD for detection. Barbarossa[4-5] studied the cross-terms suppression, optimal detection and parameter estimation using combined Wigner-Hough transforms (WHT), further used it to analyze the mono- or multi-component linear frequency modulation (LFM) signals. Flandrin [6] designed the time-frequency receivers for locally optimal detection. Kwok and Jones [7] estimated instantaneous frequency (IF) using an adaptive short-time Fourier transform. Chen[8] finished multi-component LFM signal detection and parameter estimation based on Radon-HHT. However, it is not an easy task to detect the phase discontinuity of the S-cubed signal when we use the above-mentioned methods.

Another TFR called the generalized time-frequency representation of Zhao, Atlas, and Marks (ZAM-GTFR)

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was investigated to solve this problem [9-11]. The ZAM-GTFR simultaneously preserves the property of finite time support, enhances spectral peaks and suppresses cross-terms. It is shown that the ridge of the ZAM-GTFR reflects the variation of IF and some characteristic features are easy to be extracted from the 2D time-frequency plane, such as the negative peaks with respect to the phase discontinuity of discrete phase code, which is suitable for analyzing the S-cubed signal. In conclusion, we could find some useful ways for the detection and parameter estimation of the S-cubed signal from the ZAM-GTFR perspective.

We formulate the ZAM-GTFR and find an analysis approach of the stealth S-cubed radar signal. The remainder of this paper is organized as follows. Section 2 gives the model of the S-cubed signal and briefly recalls the definitions of the ZAM-GTFR and HT. In Section 3, we finish the detection of the S-cubed signal. In Section 4, we first extract the ridge of the ZAM-GTFR to estimate the initial frequency and modulation slope of LFM, and then use information of LFM to estimate the rate of discrete phase code. Section 5 shows performances of the proposed algorithm including the computation complexity, detection probability and normalized root mean squared error (NRMSE) and Section 6 presents conclusions.

2. Signal Model and Definition

2.1. Signal model

The general S-cubed signals are a kind of hybrid modulated signals which superimpose a short, cyclically repeated discrete phase code on an LFM waveform. Thus, the S-cubed signal can be denoted as

$$x_{\mathrm{c}}(t)=\frac{1}{\sqrt{NP}}\sum_{n=0}^{N-1}\sum_{p=0}^{P-1}e^{\mathrm{j}\left[2\pi\left(f_{\mathrm{c}}t+0.5Kt^2\right)+\varphi_0\right]}c_p\mu(p,n) \tag{1}$$

where $\mu(p,n)=\mu\left[\left(t-pT_1-nT_2\right)/T_1\right]$, $\mu(t)=\begin{cases}1, 0\le t<1\\0,\text{otherwise}\end{cases}$, and T_1 is the width of code, T_2 the period of code, P the length of period, and N the number of periods. f_{c} and K are the initial frequency and modulation slope of LFM, respectively. φ_0 is the initial phase and c_p the value of encoding.

Lynch[1] showed there are some guiding principles for the choice of discrete phase code which are the minimum of mismatch loss and optimum of spread spectrum. We assume that the signal adopts the typical binary discrete phase code whose mismatch is 0 dB as an example, i.e., for $c_p\in\{1,-1\}$ and P=4, the code is [1 1 −1 1].

2.2. Definition

The ZAM-GTFR of the received signal $x(t)$ with kernel $g(\tau)$ is [9]

$$\begin{aligned}C_x(t,f)&=\int_{-\infty}^{+\infty}\int_{t-|\tau|/2}^{t+|\tau|/2}g(\tau)\cdot\\&x\left(s+\frac{\tau}{2}\right)x^*\left(s-\frac{\tau}{2}\right)\mathrm{e}^{-\mathrm{j}2\pi f\tau}\mathrm{d}s\mathrm{d}\tau=\\&\int_{-\infty}^{+\infty}g(\tau)A(t,\tau)\mathrm{e}^{-\mathrm{j}2\pi f\tau}\mathrm{d}\tau\end{aligned} \tag{2}$$

where the mark $*$ stands for complex conjugation, τ and $g(\tau)$ are the time delay and the window function, respectively. $A(t,\tau)$ is the local autocorrelation function (LAF) at time t, that is,

$$A(t,\tau)=\int_{t-|\tau|/2}^{t+|\tau|/2}x\left(s+\frac{\tau}{2}\right)x^*\left(s-\frac{\tau}{2}\right)\mathrm{d}s \tag{3}$$

HT is a feature extraction technique used in image analysis, computer vision and digital signal processing[12-14]. It uses a new coordinate (ρ,θ) to concentrate straight lines. When lines exist, $H_x(\rho,\theta)=\mathrm{HT}\{C_x(t,f)\}$ computes the integration over all the lines. So we can say HT is only a mapping of coordinate from (t,f) to (ρ,θ) essentially. The relationship is

$$\rho=t\cos\theta+f\sin\theta \tag{4}$$

Arranging Eq. (4) yields

$$\rho=\sqrt{t^2+f^2}\sin\left(\theta+\arctan\frac{t}{f}\right) \tag{5}$$

For a fixed point in (t,f), there is a sine curve in (ρ,θ) corresponding to it. On the one hand, if there is a straight line in (t,f), the sine curves mapping from the points of this line will intersect at one point just like integration. Intersection makes the accumulation of energy which leads to a sharp peak. On the other hand, the random noise distributes throughout the plane, therefore it cannot intersect to form a peak. In this case, we can extract the sharp peak as a feature to detect the presence of the S-cubed signal in noise.

3. Signal Detection

Because of the good performance in spread spectrum, it is a challenge to process the intercepted S-cubed signal. In this case, we study the ZAM-GTFR. It has the cone-shaped kernel and has been shown to generate quite good TFR in comparison to other approaches. Asymptotically, the ZAM-GTFR is shown to produce results identical to that of the spectrogram for stationary signals. Moreover, the ZAM-GTFR is able to drastically attenuate interference terms which are normally presented in many TFRs and has the ability to track phase discontinuity. When a signal is subjected to white noise, the ZAM-GTFR produces an unbiased estimate[10]. So the ZAM-GTFR is a potential technology that could be used to analyze the S-cubed signal.

In order to detect the S-cubed signal and estimate the initial frequency and modulation slope, firstly we can compute the square of the signal to eliminate phase discontinuity.

The square of $x_{\mathrm{c}}(t)$ is

$$x_{\mathrm{c}}^2(t)=\mathrm{e}^{\mathrm{j}\left[4\pi(f_{\mathrm{c}}t+0.5Kt^2)+2\varphi_0\right]} \tag{6}$$

and the LAF is

$$\begin{aligned}A_{x_{\mathrm{c}}^2}(t,\tau)=\int_{t-|\tau|/2}^{t+|\tau|/2}x_{\mathrm{c}}^2(s+\tau/2)x_{\mathrm{c}}^{*2}(s-\tau/2)\mathrm{d}s=\\ \int_{t-|\tau|/2}^{t+|\tau|/2}\mathrm{e}^{\mathrm{j}(4\pi f_{\mathrm{c}}\tau+4\pi K\tau s)}\mathrm{d}s=\\ \frac{\mathrm{e}^{\mathrm{j}\tau(4\pi Kt+4\pi f_{\mathrm{c}})}\sin\left(2\pi K\tau|\tau|\right)}{2\pi K\tau}\end{aligned} \tag{7}$$

To simplify the derivation, we choose rectangular window function $g(\tau)$. Thus, the ZAM-GTFR of $x_{\mathrm{c}}^2(t)$ is

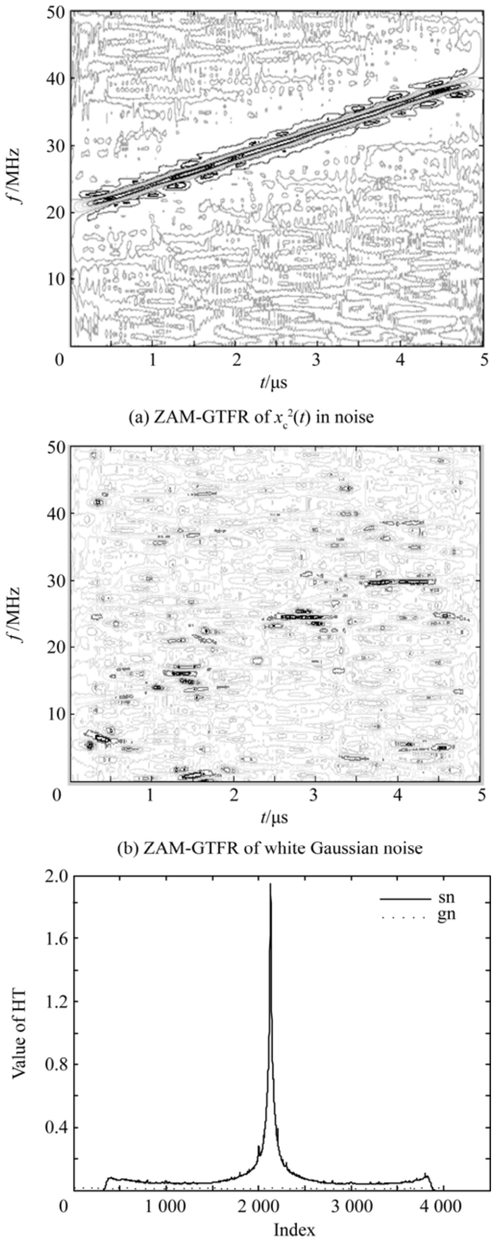
$$\begin{aligned}C_{x_{\mathrm{c}}^2}(t,f)=\\ \int_{-\infty}^{+\infty}\frac{\mathrm{e}^{\mathrm{j}\tau(4\pi Kt+4\pi f_{\mathrm{c}})}\sin\left(2\pi K\tau|\tau|\right)}{2\pi K\tau}\mathrm{e}^{-\mathrm{j}2\pi f\tau}\mathrm{d}\tau=\\ \delta(f-2f_{\mathrm{c}}-2Kt)\otimes R_{x_{\mathrm{c}}^2}(f)=\\ R_{x_{\mathrm{c}}^2}(f-2f_{\mathrm{c}}-2Kt)\end{aligned} \tag{8}$$

where $\otimes$ denotes the convolution and

$$R_{x_{\mathrm{c}}^2}(f)=\int_{-\infty}^{+\infty}\frac{\sin(2\pi K\tau|\tau|)}{2\pi K\tau}\mathrm{e}^{-\mathrm{j}2\pi f\tau}\mathrm{d}\tau=$$
$$\frac{1}{4|K|}-\frac{f^2}{2K^2}\cdot{}_2F_3\left(a_1,a_2;b_1,b_2,b_3;z\right)$$

with ${}_2F_3(a_1,a_2;b_1,b_2,b_3;z)=\sum_{n=0}^{+\infty}\frac{(a_1)_n(a_2)_n z^n}{(b_1)_n(b_2)_n(b_3)_n n!}$, which is the generalized hypergeometric function with $(\lambda)_n=\lambda(\lambda+1)(\lambda+2)\cdots(\lambda+n-1),(\lambda)_0=1$ and $a_1=1/2$, $a_2=1$, $b_1=3/4$, $b_2=5/4$, $b_3=3/2$, $z=-(\pi^2 f^4)/(16K^2)$. According to Ref. [11], the envelopes of $R_{x_{\mathrm{c}}^2}(f)$ decay with the increase of $|f|$ and the maxima of $R_{x_{\mathrm{c}}^2}(f)$ are maintained at $f=0$.

Observed from Eq. (8), the ZAM-GTFR of the $x_{\mathrm{c}}^2(t)$ simultaneously preserves the property of finite time support and strengthens spectral peaks. It has approximately ideal property of time-frequency concentration, i.e., the energy concentrates on the straight line which represents the IF of $x_{\mathrm{c}}^2(t)$, $f(t)=2f_{\mathrm{c}}+2Kt$. Hence $H_{x_{\mathrm{c}}^2}(\rho,\theta)=\mathrm{HT}\{C_{x_{\mathrm{c}}^2}(t,f)\}$ can extract this line to form a sharp peak which indicates that there is a signal in noise. The simulation results of processing are shown in Fig. 1. In the simulation, $f_{\mathrm{c}}=20$ MHz, $K=4\times10^{12}$, SNR=5 dB, and the duration is 5 μs.



(a) ZAM-GTFR of $x_{\mathrm{c}}^2(t)$ in noise

(b) ZAM-GTFR of white Gaussian noise

(c) HT value of ZAM-GTFR

Fig. 1 S-cubed detection.

where "sn" and "gn" stand for the HT value of ZAM-GTFR $x_{\mathrm{c}}^2(t)$ in noise and white Gaussian noise, respectively.

4. Parameter Estimation

4.1. Initial frequency and modulation slope estimation

The ridge of the ZAM-GTFR reflects important information about the characteristics of the S-cubed signal [15-16]. We introduce an algorithm to extract the ridge. The procedure is to search for the maxima of $C_x(t,f)$ along f. Therefore, the ridge of $C_x(t,f)$ could be defined as

$$r(t)=\arg\max_f\{C_x(t,f)\} \tag{9}$$

Since the maxima of $R_{x_c^2}(f-2f_c-2Kt)$ locate at $f(t)=2f_c+2Kt$, the ridge of $C_{x_c^2}(t,f)$ is a slope which stands for the IF, i.e.,

$$r(t)=f(t)=2f_c+2Kt \tag{10}$$

Then we do polynomial curve fitting to $r(t)$ using the least squares[17-18]. The cost function is

$$\sum_{i=1}^{I}(\hat{r}_i-r_i)^2=\left\|\hat{\boldsymbol{r}}-\boldsymbol{r}\right\|_2 \tag{11}$$

The problem of curve fitting is to solve the minimum of the cost function. Particularly, for linear fitting, the polynomial coefficients can be computed by

$$\hat{d}_1=\frac{\sum_{i=1}^{I}t_i\cdot r_i-I\overline{t}\cdot\overline{r}}{\sum_{i=1}^{I}t_i^2-I\left(\overline{t}\right)^2} \tag{12}$$

$$\hat{d}_0=\overline{r}-\hat{d}_1\overline{t} \tag{13}$$

where $\overline{t}=\frac{1}{I}\sum_{i=1}^{I}t_i$ and $\overline{r}=\frac{1}{I}\sum_{i=1}^{I}r_i$ are the arithmetic mean of t and r, respectively, I is the length of signal. Then, the model is

$$\hat{r}(t)=\hat{d}_0+\hat{d}_1t \tag{14}$$

Furthermore, the estimates of f_c and K can be described as $\hat{f}_c=\hat{d}_0/2$, $\hat{K}=\hat{d}_1/2$.

4.2. Discrete phase code rate estimation

Utilizing the estimation of K, we can generate the reconstructing signal as

$$s_d(t)=e^{j\pi\hat{K}t^2} \tag{15}$$

In order to study the feature caused by phase discontinuity, we only pay attention to two different codes and the signal contains only one period. Then the original signal $x_c(t)$ can be simply rewritten to

$$x_c(t)=\left[U(t_0-t)-U(t-t_0)\right]e^{j\left[2\pi(f_ct+0.5Kt^2)+\varphi_0\right]} \tag{16}$$

where $U(t)=\begin{cases}1, t\geq 0\\ 0, \text{otherwise}\end{cases}$, and t_0 is the time of phase discontinuity.

Multiplying $x_c(t)$ with the conjugation of $s_d(t)$, we have

$$\begin{aligned}&y(t)=x_c(t)s_d^*(t)=\\&\left[U(t_0-t)-U(t-t_0)\right]e^{j\left\{2\pi\left[f_ct+0.5\left(K-\hat{K}\right)t^2\right]+\varphi_0\right\}}=\\&\left[U(t_0-t)-U(t-t_0)\right]e^{j\left[2\pi\left(f_ct+0.5\Delta Kt^2\right)+\varphi_0\right]}\end{aligned} \tag{17}$$

then

$$\begin{aligned}&A_y(t,\tau)=\int_{t-|\tau|/2}^{t+|\tau|/2}y(s+\tau/2)y^*(s-\tau/2)ds=\\&\int_{t-|\tau|/2}^{t+|\tau|/2}\left[U(t_0-s-\tau/2)-U(s+\tau/2-t_0)\right]\cdot\\&e^{j[2\pi f_c(s+\tau/2)+2\pi\Delta K(s+\tau/2)^2/2]}\left[U(t_0-s+\tau/2)-\right.\\&\left.U(s-\tau/2-t_0)\right]e^{-j[2\pi f_c(s-\tau/2)+2\pi\Delta K(s-\tau/2)^2/2]}ds=\\&e^{j2\pi f_c\tau}\cdot\int_{t-|\tau|/2}^{t+|\tau|/2}\left[U(t_0-s-\tau/2)-U(s+\tau/2-t_0)\right]\cdot\\&\left[U(t_0-s+\tau/2)-U(s-\tau/2-t_0)\right]e^{j2\pi\Delta K\tau s}ds\end{aligned} \tag{18}$$

If the error of $\hat{K}$ is small, $\Delta K\approx 0$.

$$\begin{aligned}&A_y(t,\tau)=e^{j2\pi f_c\tau}\cdot\\&\int_{t-|\tau|/2}^{t+|\tau|/2}\left[U(t_0-s-\tau/2)-U(s+\tau/2-t_0)\right]\cdot\\&\left[U(t_0-s+\tau/2)-U(s-\tau/2-t_0)\right]ds\end{aligned} \tag{19}$$

From Ref. [11], we have $C_y(t,f)\approx C_m(f-f_c)\cdot V(t,f-f_c)$ with $V(t,f)=1-2\cos(2\pi f|t-t_0|)$, where $C_m(f)$ is the ZAM-GTFR of monopulse. Because the energy of $C_m(f-f_c)$ is concentrated at $f=f_c$, we could just consider $C_y(t,f)$ around f_c. When $t=t_0$, $V(t,f-f_c)$ gets the minimum −1, and $C_y(t,f_c)\approx -C_m(0)$, where $C_m(0)$ is positive. When $t\neq t_0$ and f is nearby f_c, $V(t,f-f_c)$ increases with the increase of $|(f-f_c)(t-t_0)|$. As a result, there would be a negative peak around the point (t_0, f_c) and the value of this peak may be nearly equal to $C_m(0)$.

Based on the analysis above, we can extract the negative peaks as a useful feature to estimate the rate of discrete phase code. Specific steps are as follows:

Step 1 Extract the negative peaks denoted as $N_p(t)$ from the ZAM-GTFR of $y(t)$.

Step 2 Compute fast Fourier transform (FFT) of $N_p(t)$.

Step 3 Because the locations of negative peaks indicate the time of phase discontinuity, the base frequency f_b of Fourier spectrum is equal to the rate of discrete phase code f_r. Thus, we can search within the spectrum to obtain the estimate of f_r, $\hat{f}_r=f_b$.

5. Performance Analysis

5.1. Estimation of computation complexity

Assume L is the length of frequency bins, and M is the length of window, $M=2L+1$.

The square of the signal to eliminate phase discontinuity needs I complex multiplications.

In Ref. [9], Zhao, et al. discussed the discrete form of ZAM-GTFR:

$$C_x(n,m;\phi)= 2\sum_{n'=n-L}^{n+L}\sum_{k=-L}^{L}\phi(n-n',k)x(n'+k)\cdot x^*(n'-k)\mathrm{e}^{-\mathrm{j}(2\pi/M)mk}, |m|\le L \tag{20}$$

Meanwhile, they pointed out that the discrete ZAM-GTFR can be formulated as the real part of a standard discrete Fourier transform (DFT) which can be computed by an FFT of radix 2 [19] without affecting the realness of the ZAM-GTFR.

$$C_x(n,m;\phi)=4\,\mathrm{Re}(\sum_{k=0}^{L}\hat{g}(k)y(n,k)\mathrm{e}^{-\mathrm{j}k\theta}) \tag{21}$$

where $y(n,k)=\sum_{p=-|k|}^{|k|}x(n-p+k)x^*(n-p-k)$, $\theta=(2\pi/M)m$ and $\hat{g}(k)=\begin{cases}0.5g(k),k=0\\ g(k),\text{otherwise}\end{cases}$ is the window function. From Eq. (21), we can know that the ZAM-GTFR needs $[(M\text{-}1)I\log_2 I]/4$ complex multiplications.

Polynomial curve fitting in this paper needs $2I+7$ complex multiplications approximately. Extracting the information of discrete phase code needs I complex multiplications, using FFT to compute code rate $[I\log_2 I]/2$.

Table 1 gives out the computation complexity including complex additions.

Tabel 1 Computation complexity

Processing	Complex addition	Complex multiplication
Square	0	I
ZAM-GTFR	$[(M-1)I\log_2 I]/2$	$[(M-1)I\log_2 I]/4$
Fitting	$4I-1$	$2I+7$
Code rate	$I\log_2 I$	$[I\log_2 I]/2+I$
Total	$[(M+1)I\log_2 I]/2+4I-1$	$[(M+1)I\log_2 I]/4+4I+7$

5.2. Simulation

In this simulation, the sampling frequency is 1 GHz and the code-width of discrete phase code is 15 ns. Both the initial frequency and bandwidth of LFM are 100 MHz. The noise is white and Gaussian. The SNR values vary from −5 dB to 15 dB. Different signals are tested for 200 times in each SNR.

Figure 2 shows the results of the detection probability for various SNRs and for several values of period number. The number of periods (N) is 1, 2, 3. With the same discrete phase code, if the number of periods is larger, the points which are used for detection are more. The energy from the ZAM-GTFR of these points is larger, therefore, the HF value of ZAM-GTFR is larger and the detection threshold which is proportional to the noise energy. To provide the same probability, the threshold may be higher and then the SNR will be lower. So, according to Fig. 2, the probability of detection increases with the increase of period number at the same SNR, meanwhile the required SNR is lower for the larger number of periods to provide the same probability of detection.

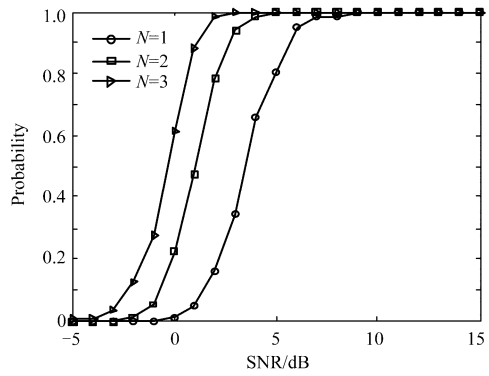


Fig. 2 Detection probability.

Under the same signal model, there is no similar algorithm of parameter estimation. Figures 3-4 only show the estimations of f_c and K mentioned in this paper and Ref. [5]. The number of periods is 8. Illustrated by Figs. 3-4, the WVD has the higher estimation accuracy of f_c and K due to the better time-frequency aggregation. However, it has a significant problem of high noise sensitivity. The ZAM-GTFR overcomes this problem more or less in the presence of white noise and generates an unbiased estimate[10]. It is shown that improved anti-noise performance can be obtained by the ZAM-GTFR, though the accuracy of parameter estimation decreases slightly. In summary, the ZAM-GTFR achieves a balance between the accuracy of parameter estimation and noise effect to finish the estimation at a lower SNR. Here, the NRMSE is defined as

$$\mathrm{NRMSE}=\frac{\sqrt{\frac{1}{S_\mathrm{T}}\sum_{\kappa=1}^{S_\mathrm{T}}(\varsigma_\kappa-\varsigma)^2}}{\varsigma} \tag{22}$$

where S_T is the experiment time, ς the parameter to be estimated, and ς_κ the estimation value .

Moreover, we recommend matched signal transform (MST) to have a performance contrast. MST is initially designed to localize TV signals with nonlinear phase at their modulation slope parameter. This localization is a result of choosing the nonlinear characteristic basis function $\eta(t)$ of the transform to match, in time-frequency structure, the phase function of the analysis signal. In this paper, since the S-cubed signal contains the LFM modulation and has the nonlinear phase, we make $\eta(t)=t^2$ in the MST which is appropriate [20].

Observed from Fig. 5, we can know that the MST algorithm has greater advantage at higher SNR but is easy to be influenced by the noise because of the main lobe characteristics and lost the initial frequency information as a two-dimensional transform. The ZAM-GTFR algorithm is based on the extraction of ridge line which mostly depends on the design of cone-shaped kernels.

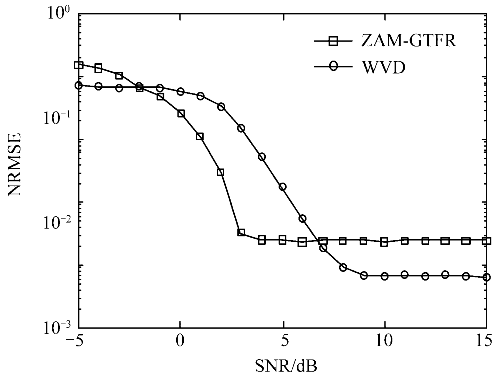


Fig. 3 NRMSE of initial frequency by GTFR.

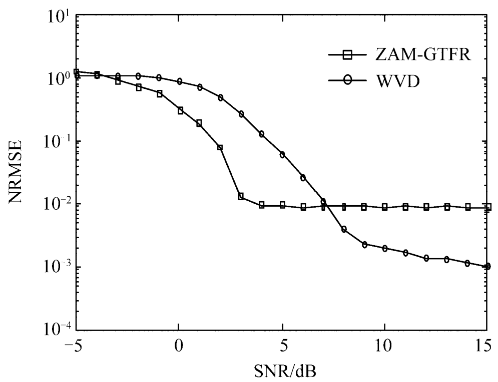


Fig. 4 NRMSE of modulation slope by GTFR.

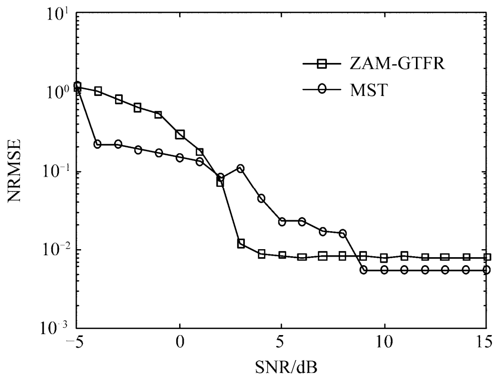


Fig. 5 NRMSE of modulation slope by MST.

Figures 6-7 show this algorithm is feasible when S-cubed signal is subjected to colored noise, Rayleigh clutter and K-distribution clutter.

Figure 8 shows the NRMSE of the estimation of f_r for various SNR and for several values of period number, respectively. The number of periods is 8, 9 and 10. Illustrated in Fig. 8, the NRMSE is less than 10^{-2} when the SNR is greater than 3 dB. Since negative peaks of the ZAM-GTFR characterize the phase discontinuity, the estimation of f_r performances well.

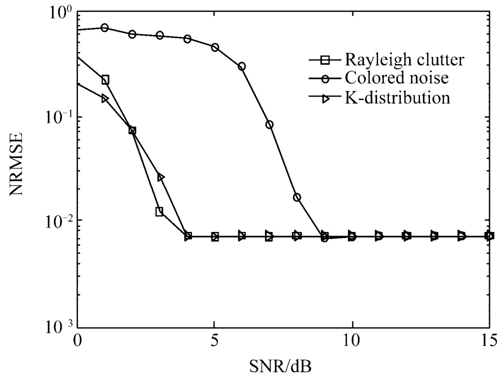


Fig. 6 NRMSE of initial frequency.

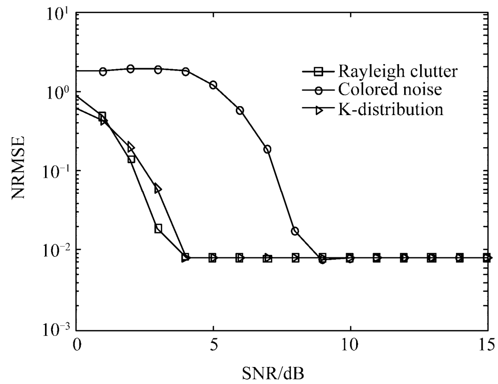


Fig. 7 NRMSE of modulation slope.

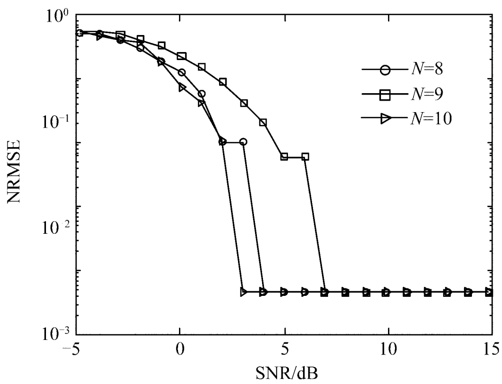


Fig. 8 NRMSE of code rate.

6. Conclusions

We have explored an approach of signal detection and parameter estimation of the S-cubed signal. The HT is used to extract the characteristic feather to detect the signal. The ridge of the ZAM-GTFR is used to compute the IF, and polynomial curve fitting of IF is used to estimate the initial frequency and modulation slope of LFM. The locations of phase discontinuity are detected by extracting the negative peaks of the ZAN-GTFR. The rate of discrete phase code is acquired by FFT. The presented algorithm has higher accuracy of parameter estimation when the SNR is above 3 dB.

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