Performance Evaluation for Unknown Deterministic Target Signals Detection via Detection Information

Xiaolong KONG [1], Daxuan ZHAO [1], Nan WANG [1], Dazhuan XU [1,2]

[1] Nanjing University of Aeronautics and Astronautics, 210000, Nanjing, China
[2] The Purple Mountain Laboratories, 211100, Nanjing, China

Xiao_long_kong@nuaa.edu.cn, zhaodaxuan@nuaa.edu.cn, n_wang@nuaa.edu.cn, dazhuan_xu@163.com

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Abstract. *The detection method, such as Newman-Pearson (NP) method, can provide an accurate prediction for the performance of target detection under all signal-to-noise ratio regions. However, the performance limits of radar signal detection have not been extensively studied yet. In this paper, we propose a novel detection method for unknown deterministic signals in radar system, which utilizes mutual information to characterize the uncertainty of the existence state of signal. The a posteriori probability density function of existence state of signal can be directly obtained via the Bayesian framework, ensuring that there is no loss of information regarding to the target's existence state during the mutual information computation process. Numerical simulations show that the proposed method exhibits superior detection performance compared to the NP detection method.*

Keywords

Energy detection, detection information, information theory, probability density function, unknown deterministic signals

1. Introduction

Radar signal detection refers to determining whether the target exists in the observation interval, which is an important step in radar target detection field [1], [2]. When identifying whether there is a target signal in the observation interval, there are commonly two assumptions for the received signal. Suppose H_0, the received signal is the noise signal, suppose H_1, the received signal is the sum of the target signal and the noise signal [3], [4]. When the target signal and noise signal have a known deterministic form, it appears suitable to use the matching filter [5]. When the target signal has an unknown deterministic form, a commonly used method is to treat the signal as a sample function of random process.

For the target signal with a known deterministic form, researchers have proposed many valuable detection methods. In [6], a generalized likelihood ratio test spectrum sensing scheme is proposed for detecting the presence of target signals. In [7], an exact solution for optimal detection of known signals in Gaussian noise through sparse sampling is presented using dynamic programming. Conversely, research on target signals with unknown deterministic forms seems to be relatively sparse among scholars. In fact, under the assumption of Gaussian white noise, even if the form of the signal is unknown, the deterministic assumption suggests that the input of the signal is Gaussian distribution with a non-zero mean. Therefore, under the condition of lacking *a priori* information about the target signal form, it seems appropriate to utilize the energy of the signal to determine the presence of the target signal [8]. The energy detector accumulates the received signal energy over a specified observation time window and compares it to a predefined threshold to determine target signal presence. The energy detection was first proposed for the scenario of detecting deterministic target signals transmitted over flat, band-limited Gaussian noise channels [9]. It should be emphasized that the detection statistic is the cumulative energy of the signal in the observation zone, which has nothing to do with the signal's shape. Therefore, energy detection method is a blind detection method, and it is suitable for any unknown deterministic target signals [10], [11].

It is assumed that the noise signal has a flat, band-limited power spectral density. When only the noise signal is present in the observation interval, through Nyquist sampling, the energy of the noise signal can be approximated as the sum of squares of independent random variables with zero mean and equal variance. The sum follows a central chi-square distribution. When unknown deterministic target signal is present in the observation interval, through Nyquist sampling, the energy can be approximated as the sum of squares of independent random variables. The sum follows a non-central chi-square distribution, where the parameter is equal to the total energy of the unknown deterministic target signal [9]. Many researchers have also carried out relevant verifications regarding to the approximation of signal energy. In [12], based on the Karhunen-Loeve expansion, an expression for the energy distribution is derived. Numerical simulations demonstrate that the chi-square approximation is a good approximation, particularly for large time-bandwidth product values. To further validate the feasibility of the approximation, Grenander proposes a new method that accurately calculates the energy distribution of Gaussian

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noise in finite-time samples [13]. He compares the exact results of several values of time-bandwidth product with the chi-square approximation (in Sec. 4.4) and concludes that even for moderate time-bandwidth product values, the approximation holds quite well.

It is common to assess the presence of a target signal in the received signal using the false alarm probability (PFA) and the detection probability (PD), such as the Neyman-Pearson (NP) detection method. In radar target signal detection [14], the PD and PFA are shown as

$$P_{\mathrm{D}} = \int_{T_{\mathrm{h}}}^{\infty} \frac{V}{\sigma^2} \exp\left(-\frac{A_{\mathrm{s}}^2 + A_{\mathrm{n}}^2}{2\sigma^2}\right) I_0\left(\frac{A_{\mathrm{s}} A_{\mathrm{n}}}{\sigma^2}\right) \mathrm{d}V, \tag{1}$$

$$P_{\mathrm{FA}} = \exp\left(-\frac{T_{\mathrm{h}}^{\;2}}{2\sigma^2}\right) \tag{2}$$

where T_{h} represents the detection threshold value, A_{S} represents the amplitude of signal, A_{n} represents the amplitude of noise, σ^2 represents the variance of noise, $I_0(\cdot)$represents the modified Bessel function of zero order.

It is shown that two probabilities are directly dependent on the detection threshold value T_{h}. T_{h} is typically determined by experienced radar personnel based on their expertise. Therefore, target detection always involves uncertainty, and theoretically, obtaining the optimal threshold is not possible. As shown in Fig. 1, it can be observed that the optimal threshold exhibits uncertainty, which should be set at a proper signal-to-noise ratio (SNR) value [14].

In [14], the mutual information is introduced to evaluate the radar received signal. The optimal threshold level is determined by maximizing mutual information. Mutual information is introduced as an evaluation metric for radar target signal detection. However, mutual information can only be computed under the given $p(v)$, PFA and PD ([14], p. 228), which leads to information loss in mutual information. The reason is that giving PFA and calculating PFA can be seen as a hard decision on the target presence state, and hard decisions result in the loss of some signal information [15].

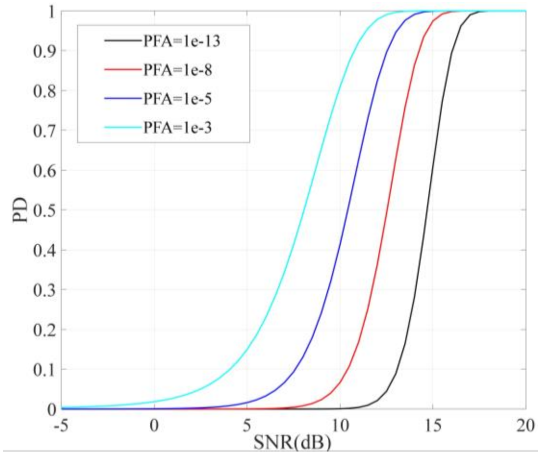

Fig. 1. The relationship between the SNR and PFA under different PFA scenarios.

Intact Form	Abbreviated
Information Theory	IT
Newman-Pearson	NP
Probability Density Function	PDF
Detection Probability	PD
False Alarm Probability	PFA
Receiver Operating Characteristic	ROC
Signal-to-Noise Ratio	SNR

Tab. 1. Abbreviations list.

This paper considers the energy detection problem of unknown deterministic target signal and then proposes an information theory (IT) method to obtain the maximum mutual information. The main contributions of this paper are as follows

First, compared to NP detection methods, this paper presents the theoretical limits of mutual information. Then, other target detection algorithms, such as CenterNet and state-of-the-art model, can also leverage mutual information for evaluation, enabling a more comprehensive assessment of algorithm performance. Finally, the mutual information can serve as a novel evaluation metric, providing a benchmark for comparing various target detection algorithms or methods.

The abbreviations used in the text can be found in Tab. 1. The remainder of this manuscript is organized as follows. In Sec. 2, the system model is briefly presented for unknown deterministic radar signals. In Sec. 3, the mutual information for IT detection method is described. In Sec. 4, extensive simulation results are presented to demonstrate the performance of the IT detection method. Finally, conclusions are drawn in Sec. 5.

2. System Model

The radar target signal detection problem is essentially a binary hypothesis problem. The output signal of the radar can be described as

$$z(t) = \begin{cases} s\varphi(t-\tau) + w(t), H_1 \\ w(t), \qquad\qquad\quad H_0 \end{cases}, t = 1, \cdots, T \tag{3}$$

where s means the scattering coefficient of the target signal, $\varphi(t-\tau)$ represents the received unknown deterministic target signal. $w(t)$ denotes complex Gaussian noise of a limited bandwidth $B/2$ with zero mean and variance σ^2.

Substituting the existence state variable v into (1), the binary hypothesis problem can be uniformly written as

$$z(t) = vs\varphi(t-\tau_k) + w(t), t = 1, \cdots, T \tag{4}$$

where v = 1 means that the output signal is target signal plus noise signal, and v = 0 means that the output signal is noise signal.

Applying a low-pass filter to the received signal, down-convert the received signal to baseband, and then sample it at the Nyquist rate B. The sampling sequence can be written as

$$z\left(\frac{n}{B}\right)=vs\varphi\left(\frac{n-B\tau}{B}\right)+w\left(\frac{n}{B}\right). \tag{5}$$

Since the sample rate B is high enough and the target signal energy is assumed to be virtually totally contained inside the observation interval, no signal information should be lost [11]. Without loss of generality, the sampling sequence of received signal $z(n)$ can be described as

$$z(n)=vs\varphi(n-x)+w(n), n=1,\cdots,N \tag{6}$$

where $x = B\tau$ is the normalization time delay, $N = TB$ represents the time-bandwidth product. $w(n)$ is a zero-mean complex Gaussian random variable with variance σ^2.

The energy detection method computes the total energy over a designated window [16], [17], which is given as

$$r=\sum_{n=1}^{N}\left|z(n)\right|^2=\sum_{n=1}^{N}\left|vs\varphi(n-x)+w(n)\right|^2. \tag{7}$$

Deriving an exact expression for the probability density function (PDF) of total energy r is quite complex. Nonetheless, we can achieve a concise approximation. It can be assumed that a reasonable structure for the PDF is a chi-square distribution, attributable to sampling theory [8]. Therefore, under the condition of a given target existence state variable, we derive the PDF of the output energy, which is written as

$$p(r|v)=\frac{r^{N-1}\exp\left(-\frac{r}{\sigma^2}\right)}{\left(\sigma^2\right)^N\Gamma(N)}\exp\left(-v\rho^2\right){}_0F_1\left(;N;\frac{vr}{\sigma^2}\rho^2\right) \tag{8}$$

where ${}_0F_1\left(;N;\frac{vr}{\sigma^2}\rho^2\right)$ is hypergeometric function. $\rho^2=\lambda/\sigma^2$ is the SNR. λ is the target signal energy in observation interval.

Equation (8) provides a unified form for energy detection of an unknown deterministic target signal, which is a new expression. When the output signal is the noise signal, the total energy r approximately follows a chi-squared distribution, and (8) is simplified as

$$p(r|v=0)=\frac{r^{N-1}\exp\left(-\frac{r}{\sigma^2}\right)}{\left(\sigma^2\right)^N\Gamma(N)}. \tag{9}$$

When the output signal is target signal and noise signal, the total energy r approximately follows a non-central chi-squared distribution, and (8) is simplified as

$$p(r|v=1)=\frac{r^{N-1}\exp\left(-\frac{r}{\sigma^2}\right)}{\left(\sigma^2\right)^N\Gamma(N)}\exp\left(-\rho^2\right){}_0F_1\left(;N;\frac{r}{\sigma^2}\rho^2\right). \tag{10}$$

3. Mutual Information in Output Signal

We first consider the *a priori* distribution $p(v)$ of the target's presence. When the target existence state variable is v and the radar output energy is r, the joint PDF $p(r, v)$ can be defined [14]. According to the definition of the entropy, the *a priori* entropy in the observation field is expressed as

$$\begin{aligned}H(v)&=-\sum_{v}p(v)\log p(v)\\&=-p(1)\log_2 p(1)-\left(1-p(1)\right)\log_2\left(1-p(1)\right)\end{aligned} \tag{11}$$

where $p(1)$ represents the *a priori* probability of the target signal's presence in the observation interval, with a range value of [0,1].

Figure 2 depicts the relationship between *a priori* entropy and the *a priori* existence probability. It can be observed that the *a priori* entropy is maximized when the *a priori* existence probability is 0.5. This is because when all possible outcomes are equally likely, the system's uncertainty reaches its maximum, resulting in maximum entropy. On the other hand, when the *a priori* probability is 0 or 1, the *a priori* entropy is minimized. This is because the target state is already determined, leading to the least uncertainty in the system and minimum entropy.

Next, we also need to consider the measurement of uncertainty in the existence state contained in the output energy. The *a posteriori* PDF is a probability distribution of parameters obtained based on received data, which can provide an estimate of the most probable value of the existence state and their associated uncertainty. We derive *a posteriori* PDF of the target existence state, which is expressed as

$$\begin{aligned}p(v|r)&=\frac{p(r,v)}{p(r)}\\&=\frac{p(v)p(r|v)}{p(0)p(r|0)+p(1)p(r|1)}.\end{aligned} \tag{12}$$

Substituting (8) into (12), we have

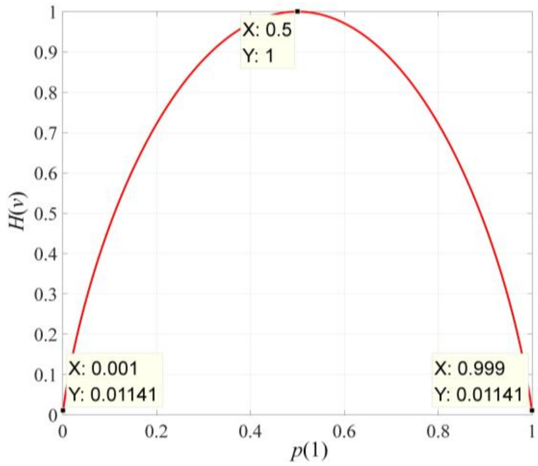

Fig. 2. The relationship between *a priori* entropy and signal existence probability.

$$p(v|r)=\frac{p(v)\Upsilon(r|v)}{p(0)+p(1)\Upsilon(r|1)} \tag{13}$$

where

$$\Upsilon(v,r)=\exp\left(-v\rho^2\right){}_0F_1\left(;N;\frac{vr}{\sigma^2}\rho^2\right). \tag{14}$$

The *a posteriori* entropy, as a measure of uncertainty in the *a posteriori* PDF, provides an evaluation of the target's existence status under the output signal is received. Similar to (11), which is written as

$$H(v|r)=-\sum_v p(v|r)\log_2 p(v|r). \tag{15}$$

Now, we calculate the mutual information. It is well known that mutual information $I(r;v)$ quantifies the degree of dependence or information shared between two random variables. According to the definition of the mutual information, it can be calculated as

$$I(r;v)=H(v)-H(v|r). \tag{16}$$

Substituting (11) and (15) into (16), we have

$$\begin{aligned}I(r;v)=&-p(1)\log_2 p(1)-\left(1-p(1)\right)\log_2\left(1-p(1)\right)\\&-p(1|r)\log_2 p(1|r)-p(0|r)\log_2 p(0|r).\end{aligned} \tag{17}$$

It is obvious that the target detection process is essentially a process of getting information about the target existence state. Equation (17) represents the uncertainty of the existence state v under the given the output energy r condition. A superior detection method should be able to obtain more mutual information [18], [19]. This can have a greater impact on the results of target detection or recognition. We can evaluate performance of different detection methods via detection information.

In addition, the PFA and PD are two decision probabilities universal in radar target detection field. Therefore, we also derive the PFA and the PD of the IT detection method. The PFA is calculated as

$$\begin{aligned}P_{\mathrm{FA}}&=E\left[\frac{p(1)\Upsilon(1,r_0)}{p(0)+p(1)\Upsilon(1,r_0)}\right]\\&=E\left[\frac{p(1)\exp\left(-\rho^2\right){}_0F_1\left(;N;\frac{\lambda}{N_0}\rho^2\right)}{p(0)+p(1)\exp\left(-\rho^2\right){}_0F_1\left(;N;\frac{\lambda}{N_0}\rho^2\right)}\right].\end{aligned} \tag{18}$$

The PD is calculated as

$$\begin{aligned}P_{\mathrm{D}}&=E\left[\frac{p(1)\Upsilon(1,r_1)}{p(0)+p(1)\Upsilon(1,r_1)}\right]\\&=E\left[\frac{p(1)\exp\left(-\rho^2\right){}_0F_1\left(;N;\frac{\lambda}{N_0}\rho^2\right)}{p(0)+p(1)\exp\left(-\rho^2\right){}_0F_1\left(;N;\frac{\lambda}{N_0}\rho^2\right)}\right].\end{aligned} \tag{19}$$

4. Results & Discussion

4.1 NP Detection Method

As mentioned in the introduction, the total energy of noise signal in the observation interval approximately follows a chi-squared distribution, while the total energy with target signal presence approximately follows a non-central chi-squared distribution. Non-central chi-squared tables are neither as widespread nor as convenient as central chi-squared tables, necessitating the use of approximations instead. According to the central limit theorem, as the degrees of freedom increase, the shape of the chi-squared distribution approaches that of a Gaussian distribution. This occurs because the distribution's peak becomes sharper and more concentrated around the mean, with increased symmetry. This approximation is particularly useful in practical applications, especially when dealing with large samples or complex statistical analyses, as it allows for the use of Gaussian distribution properties to simplify calculations and derivations in high degrees of freedom scenarios. Meanwhile, Urkowitz also noted that the PDF of the detection statistic can be approximated using a Gaussian distribution when time-bandwidth product N is large [9].

Therefore, under the noise signal condition, the detection statistic is distributed as a Gaussian variate $N(N\sigma^2; N\sigma^4)$ [16]. The PFA for NP detection method can be expressed as

$$\begin{aligned}P_{\mathrm{FA}}&=\int_{T_{\mathrm{h}}}^{+\infty}\frac{1}{\sqrt{2\pi N\sigma^4}}\exp\left\{-\frac{(r-N\sigma^2)^2}{2N\sigma^4}\right\}\mathrm{d}r\\&=Q\left(\frac{T_{\mathrm{h}}-N\sigma^2}{\sqrt{N\sigma^4}}\right)\end{aligned} \tag{20}$$

where

$$Q(x)=\frac{1}{\sqrt{2\pi}}\int_x^{\infty}\exp\left\{-\frac{t^2}{2}\right\}\mathrm{d}t \tag{21}$$

Under the target signal condition, the detection statistic is distributed as a Gaussian variate $N(N\sigma^2+\lambda; N\sigma^4+2\lambda\sigma^2)$. The PD for NP detection method can be expressed as

$$P_{\mathrm{D}}=\int_{T_{\mathrm{h}}}^{+\infty}\frac{\exp\left\{-\frac{\left(r-\left(N\sigma^2+\lambda\right)\right)^2}{2\left(N\sigma^4+2\lambda\sigma^2\right)}\right\}}{\sqrt{2\pi\left(N\sigma^4+2\lambda\sigma^2\right)}}\,\mathrm{d}r. \tag{22}$$

Then, the relationship between the PFA and the PD can be expressed as

$$P_{\mathrm{D}}=Q\left(\frac{\sqrt{N}Q^{-1}\left(P_{\mathrm{FA}}\right)-\rho^2}{\sqrt{N+2\rho^2}}\right). \tag{23}$$

Finally, the mutual information of the NP detection method is given by M. Kondo [14]. And it can be expressed as

$$\begin{aligned} I_{\mathrm{NP}}(r;v) &= H(v) - H(v|r) \\ &= -p(v)\log_2 p(v) - (1-p(v))\log_2(1-p(v)) \\ &\quad -(p(v)P_{\mathrm{D}} - p(v)P_{\mathrm{FA}} + P_{\mathrm{FA}})(A\log_2 A + (1-A)\log_2(1-A)) \\ &\quad -(1-p(v)P_{\mathrm{D}} + p(v)P_{\mathrm{FA}} - P_{\mathrm{FA}})(D\log_2 D + (1-D)\log_2(1-D)) \end{aligned} \tag{24}$$

where

$$A = p(v)P_{\mathrm{D}} / (p(v)P_{\mathrm{D}} - p(v)P_{\mathrm{FA}} + P_{\mathrm{FA}}), \tag{25}$$

$$D = (1-p(v))(1-P_{\mathrm{FA}}) / (1-p(v)P_{\mathrm{D}} + p(v)P_{\mathrm{FA}} - P_{\mathrm{FA}}). \tag{26}$$

4.2 Simulation Comparison

This section provides numerical simulation data to validate the performance of the IT detection method. All simulations are conducted on MATLAB R2024 platform loaded on the computer. Use the randn function in MATLAB to generate random Gaussian noise. The observation interval N is set to 128. The $p(1)$ is set to 0.5, 1e–3 and 1e–5.

For the NP detection method, the mutual information can be calculated when $p(v)$, PFA and PD is known [14]. For the IT detection method, the mutual information can be calculated using (17) when $p(v)$ is known. Figure 3 depicts the relationship between mutual information and the *a priori* existence probability. The mutual information significantly changes with the variation of the *a priori* existence probability. Regardless of changes in the *a priori* existence probability, the maximum mutual information consistently occurs at $p(1) = 0.5$, aligning with findings in the literature [14]. Simultaneously, it can be observed that the mutual information of the NP detection method is lower than that of the IT detection method.

It is generally considered that the existence probability of the target signal is unknown in the radar scene. For example, in maritime surveillance, the probability of target appearance is higher in open seas or far-sea areas, while it is lower in near-shore or coastal areas. Therefore, the relationship between detection information and the SNR is studied in different radar application scenarios. The simulation results of the IT detection method and NP detection method are shown in Fig. 4. Figure 4 illustrates the simulation results for different distinct scenarios, which correspond to a high probability scenario of target presence and a low probability scenario of target presence, respectively.

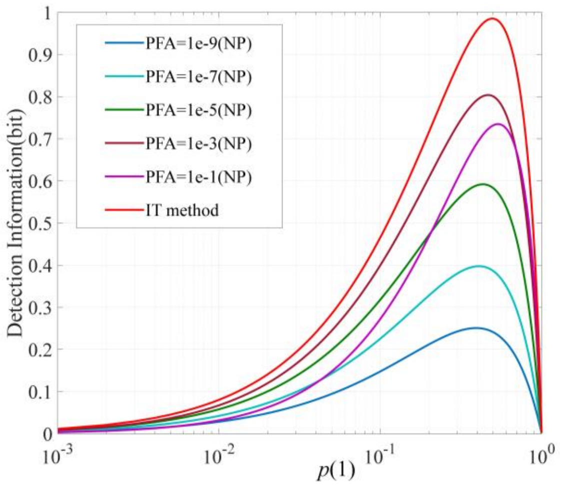

Fig. 3. The relationship between detection information and target existence probability.

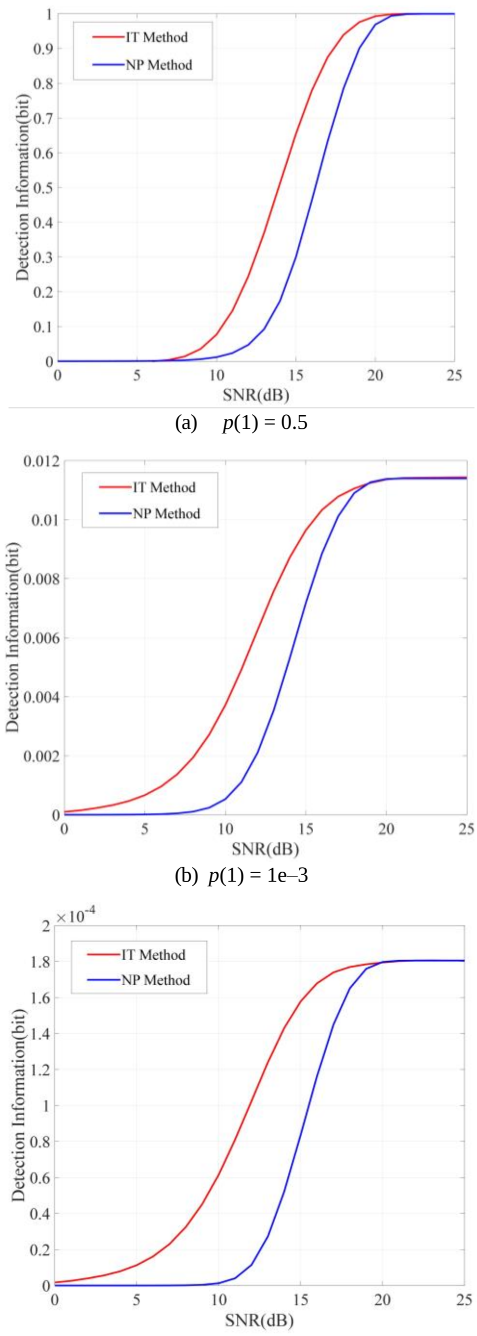

Fig. 4. The relationship between detection information and the SNR.

Note that in each scenario, the simulation results consistently demonstrate the efficacy of the IT detection method. Simulation results lead to the inference that the IT detection method offers the theoretical detection limit for unknown deterministic radar target signal, whereas neither the NP detection method can achieve this theoretical limit.

Detection scenarios	NP detection method	IT detection method
	Time consumption (s)	
$p(1)$ = 5e–1	0.105	0.073
$p(1)$ = 1e–3	0.107	0.084
$p(1)$ = 1e–5	0.122	0.109

Tab. 2. Comparison of calculation time.

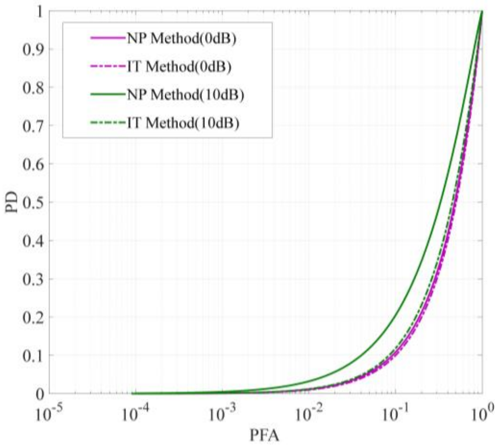

Fig. 5. The ROC for the IT detection method and the NP detection method.

In addition, the computational cost is crucial for real-time radar applications. Table 2 presents the time consumption of the IT detection method and the NP detection method under the three detection scenarios. Compared with the NP detection method, it can be observed that the calculation time of the IT detection method is slightly shorter.

Finally, we also provide the receiver operating characteristic (ROC) curve for the IT detection method and the NP detection method. The PFA and PD of the IT detection method are calculated from (18) and (19), respectively. The PFA and PD of the NP detection method are calculated from (23). From Fig. 5, it can be seen that the NP detection method demonstrates superior performance compared with the IT detection method under the framework of the PFA and PD.

5. Conclusion

In this paper, the information theory method for unknown deterministic target signal detection is proposed. The mutual information is introduced as a detection evaluation metrics for unknown deterministic radar target signal, which is defined as the mutual information between the received signal and the presence state of the target signal. The IT detection method provides a theoretical detection mutual information limit for unknown deterministic target signal. To validate the performance of the IT detection method, we derive the NP detection method as a comparison. The results indicate that the mutual information of the NP detection method is lower than the mutual information of the IT detection method. In future work, we intend to utilize the concept of mutual information to quantify the target detection performance in various radar environments, such as, multi-source conditions (beyond single-source focal points) and the non-Giannis noise (e.g., impulsive noise), aiming to translate existing theories into practical hardware implementations.

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Data Availability Statement

The mathematical model (source code) is available on request.

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About the Authors …

Xiaolong KONG received the M.E. degree in Electronic Circuit and System from the He Nan Normal University, Xinxiang, China, in 2021. He is currently pursuing the Ph.D. degree in Communication and Information System with the Nanjing University of Aeronautics and Astronautics, Nanjing, China. His research interests include broad areas of radar signal processing and information theory.

Daxuan ZHAO received the B.E. degree in Communication and Information System from the Nanjing University of Information Science and Technology, Nanjing, China, in 2022. She is currently pursuing the M.E. degree in Communication and Information System with the Nanjing University of Aeronautics and Astronautics, Nanjing, China. Her research interests include broad areas of radar signal processing and information theory.

Nan WANG received the M.E. degree in Communication and Information System from the Liaoning University of Technology, Jinzhou, China, in 2020. She is currently pursuing the Ph.D. degree in Communication and Information System with the Nanjing University of Aeronautics and Astronautics, Nanjing, China. Her research interests include broad areas of radar signal processing and information theory.

Dazhuan XU (corresponding author) received the M.E. and Ph.D. degrees in Electrical Engineering from the Nanjing University of Aeronautics and Astronautics (NUAA), Nanjing, China, in 1986 and 2001, respectively. Prof. Xu is a member of the Chinese Communication Theory and Signal Processing Committee and an Editor of the Journal of Data Acquisition and Processing.