A New Type Double-Threshold Signal Detection Algorithm for Satellite Communication Systems Based on Stochastic Resonance Technology

Xiaolin Jiang[1,2(✉)] and Ming Diao[1]

[1] Harbin Engineering University, Harbin 150000, China
jlynner@163.com
[2] Heilongjiang University of Science and Technology, Harbin 150000, China

Abstract. In order to further improve the accurate detection signal, reduce interference between signals, this paper designs a new type of signal detection algorithm for satellite communication systems, using stochastic resonance technology improve the signal-to-noise ratio of the input signal, the signal by using energy detection, double threshold, accurate judgment. The first step in the conventional energy of double threshold detection, the second step into the energy detection method based on stochastic resonance detection process. The experimental results show that this algorithm under the condition of low SNR signals effectively detect, promoted the whole satellite communication system performance.

Keywords: Satellite communication network · Stochastic resonance · Algorithm

1 Introduction

The increasing demand for wireless spectral resources in communication systems has led to an increasingly tight spectral resource, which is a bottleneck that restricts the development of wireless communications. The rapid growth of current data communication services increasingly requires satellite communication networks to have higher throughput and spectral efficiency. The current 4G satellite wireless communication network networking mode achieves full frequency multiplexing [1]. In the case of full frequency multiplexing, severe mutual interference often occurs between all the base stations transmitting the same frequency in the same frequency. The upcoming 5G satellite communication network will also adopt the same-frequency full-duplex technology, that is, in the same spectrum, the transmitting and receiving sides of the satellite communication simultaneously transmit and receive signals, and the full-duplex technology can break through the spectral resource usage restrictions of frequency division multiplexing and time division multiplexing, making the use of spectral resources more flexible. However, full-duplex technology requires extremely high interference cancellation capability, which poses a great challenge to interference cancellation technology. Effective detection of signals is the most important part of

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reducing mutual interference [2, 3]. However, in satellite communication networks, information transmission is also highly susceptible to interference such as channel decay effects, how to perform effective signal detection under low SNR conditions is directly related to the performance of the entire satellite communication network system. People began to seek a new signal detection algorithm combining multiple technologies to reduce the negative impact on signal detection reliability when the SNR caused by channel decay is low [4]. Through investigation, it is found that the stochastic resonance theory provides a good technical improvement for better signal detection under low SNR. Stochastic resonance theory states that when a stochastic resonance occurs in a noisy system, part of the noise energy is converted into the energy of the useful signal, which greatly increases the SNR of the system [5]. Based on stochastic resonance technology, this paper uses a double threshold two step algorithm to achieve signal detection, which greatly improves the overall performance of the satellite communication network.

2 Bistable Stochastic Resonance Model

The classical deterministic equation with bistable properties can be expressed as:

$$S(x) = ax - bx^3 \tag{1}$$

a and b are adjustable parameters, both greater than zero. According to this deterministic equation, the corresponding potential function of the system can be obtained as:

$$U(x) = -ax^2/2 + bx^4/4 \tag{2}$$

The waveform of this function is shown in Fig. 1. From the picture, $U(x)$ has a maximum value at $x = 0$, has two minimum values at $x = \pm\sqrt{a/b}$. Corresponding to one barrier point and two potential well points of the system, at this time, potential well depth $U_0 = a^2/4b$. We also call this the height of base (6).

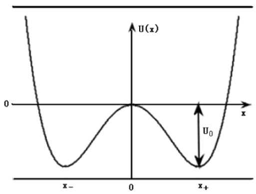

Fig. 1. Bistable system potential function characteristic curve

According to the stochastic resonance theory, if the values of a and b change, the depth and width of the well will change, but they will remain symmetrical. Given an initial state, the system will evolve differently, but will always stabilize at a certain point in $x = \pm\sqrt{a/b}$ or $x = 0$. When $a = b = 1$, the system potential function $U(x)$ and the state of the system evolve. At this time, the position of the bottom of the two symmetric wells is $x = \pm 1$, the position of the barrier is $x = 0$, and the height of the barrier is $U_0 = 1/4$.

Following, we analyze this nonlinear system, If assuming the motion of particles, if the initial value of the system is $x = 0$, the particles will stop at the unstable state of $x = 0$, until any slight interference, the particles will tend to a stable state of x_+ or x_-. If the particle is in the initial state $x < 0$, the particle will tend to the stable state of x_-. If the particle is in the initial state $x > 0$, the particle will tend to the stable state of x_+. When $t \to \infty$, the particle will stop approximating to the stable fixed point. It can be seen that the nonlinear system described by Eq. (1) has two stable states, and in the absence of the force outside the system, the system will eventually infinitely approach any one of the two stable fixed points, so Eq. (2) describes a bistable system.

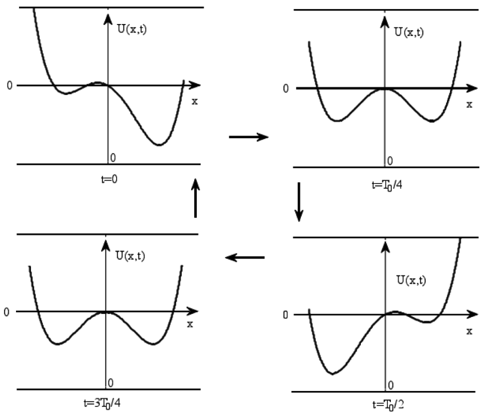

Fig. 2. Change of bistable function under plus signal driven

Under the action of external force, the system will become more complicated, but more meaningful. If the periodic signal $f(t)$ and noise $n(t)$ are added, the formula will change as

$$S(t) = ax - bx^3 + f(t) + n(t) \tag{3}$$

Physically: the particles moving in the potential well $U(x)$, the Langevin equation followed by $f(t)$ and $n(t)$. When there is an external periodic force $s(t) = A\cos\Omega t$, the potential function is modulated. In a period $T = 2\pi/\Omega$, it is apparent that the presence of a periodic external force causes the potential well to periodically tilt, as shown in Fig. 2, this tilt provides a condition for the systematic output state to cross the barrier and transition between the two potential wells, when the conditions are appropriate (7), the transition frequency is exactly equal to the periodic frequency of the signal, then the SR phenomenon occurs.

3 Algorithm Design and Analysis

Due to the random decay effects in a satellite communication environment, the energy of the user receiving other user signals at different times and at different locations is different. When the satellite communication environment between the user and other users is better, the conventional energy detection can also achieve better detection results, and the gain effect of the stochastic resonance system on the signal with better signal to noise is not obvious, so this time it is not necessary to use stochastic resonance processing. Therefore, we use a two-step signal detection improvement mechanism based on stochastic resonance.

3.1 System Model

Hypothesis test model for energy detection, whose energy detection statistic is calculated as (8)

$$T_r = \sum_{t=1}^{N} \frac{1}{N} r^2(t) \tag{4}$$

N is the number of samples. According to the central limit theorem, when the number of samples N is sufficiently large, the Tr approximation follows a normal distribution.

$$T_r \sim \begin{cases} Normal(\sigma_w^2, \frac{2}{N}\sigma_w^4), & H_0 \\ Normal(\sigma_w^2(1+\eta), \frac{2}{N}\sigma_w^4(1+\eta)^2), & H_1 \end{cases} \tag{5}$$

$\eta = \frac{h^2\sigma_s^2}{\sigma_w^2}$ is the user's received SNR. Therefore, the detection probability of energy detection can be expressed as

$$P_{D\_ED} = P(T_r > \lambda_{ED}|H_1) = Q\left(\frac{\lambda_{ED} - \sigma_w^2(1+\eta)}{\sqrt{\frac{2}{N}}\sigma_w^2(1+\eta)}\right) \tag{6}$$

False alarm probability is

$$P_{F\_ED} = P(T_r > \lambda_{ED}|H_0) = Q\left(\frac{(\lambda_{ED} - \sigma_w^2)}{\sqrt{\frac{2}{N}}\sigma_w^2}\right) \tag{7}$$

λ_{ED} is the decision threshold of energy detection. Under the Newman-Pearson criterion, when the target constant false alarm probability of a wireless communication network is given, the threshold can be obtained by the following formula.

$$\lambda_{ED} = \sqrt{\frac{2}{N}} Q^{-1}\left(\overline{P_{F\_ED}} + 1\right)\sigma_w^2 \tag{8}$$

3.2 Perceptual Mechanism Design

A new type double-threshold signal detection algorithm based on stochastic Resonance technology includes two stages of a first threshold detection and a second threshold detection. It is assumed that the channel is an AGWN fading channel, the first threshold detection phase adopts the conventional double threshold energy detection, and the second step deep detection uses the energy detection method based on stochastic resonance. The schematic is shown in Fig. 3.

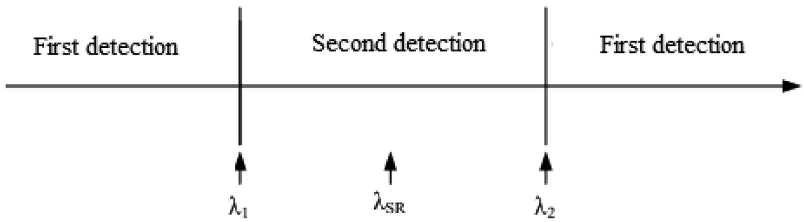

Fig. 3. Stochastic resonance, double threshold two-step sensing schematic

In the first step, the statistic is compared $(\lambda_1 < \lambda_2)$ with the two thresholds λ_1 and λ_2 to determine its reliability and whether the second step of in-depth testing is required. If the statistic of the first threshold detection is outside the interval (λ_1, λ_2), it is considered to be reliable, and the second step of in-depth detection is not required at this time. If the statistic is greater than or equal to the upper limit λ_2, the user directly determines that H_1 is established. If it is less than the lower limit λ_1, the user directly determines that H0 is true. However, when the first threshold detection statistic falls within the interval (λ_1, λ_2), the statistic is considered to be unreliable and further in-depth detection is required. Since the unreliable statistic is usually caused by weak signal under H1 condition or strong noise under H_0 condition, in the two-step signal detection, when other user signals exist, the stochastic resonance system will only process weak signals. In the second step of the in-depth detection phase, the statistics formed by the output of the stochastic resonance system will be compared to the corresponding thresholds to arrive at a decision message as to whether or not the final other user signals are present. If the statistic is greater than or equal to the threshold, it is considered that the other user is using the sensing frequency band, and the user cannot access; if the threshold is less than the threshold, the sensing frequency band is considered to be idle. The flow chart is shown in Fig. 4.

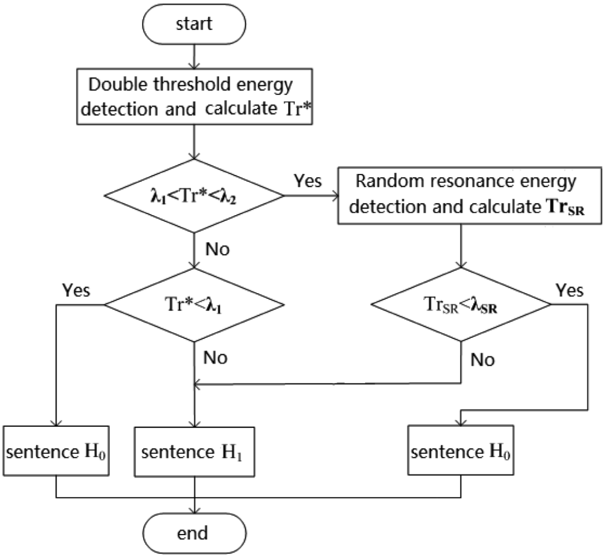

Fig. 4. Stochastic resonance, double threshold two-step Signal detection flow chart

3.3 Performance Analysis

(1) Parameter selection

The selection of thresholds plays a crucial role in the overall signal detection process. The thresholds of the first-stage sensing phase are assumed to be λ_1 and λ_2, respectively. In order to meet the requirements of the satellite communication network and fully utilize the idle frequency band, the improved perceptual algorithm based on stochastic resonance energy detection also needs to maintain a constant false alarm probability. In the following (9), Tr^* is used to represent the statistics of the first-stage sensing phase in the double-threshold signal detection algorithm based on stochastic resonance to distinguish the statistic Tr in the conventional single-level perceptual mechanism, which we discuss separately below.

Firstly, the decision threshold based on the stochastic resonance double threshold two step energy detection algorithm is discussed. Since the probability of constant false alarm is maintained, the threshold can be calculated by the Newman-Pearson criterion. However, in order to minimize the computational complexity, the lower threshold is defined as $\lambda_1 = \inf(\mathrm{Tr}^* : Tr_{SR} \geq \lambda_{SR})$, that is, the statistic after the stochastic resonance processing is greater than or equal to the minimum value of the first-order sensing phase statistic of the threshold λ_{SR}. When the statistic Tr is smaller than λ_1, it is not necessary to introduce a stochastic resonance process because the stochastic resonance process does not improve the performance of signal detection at this time. Under the Newman-Pearson criterion, the improved signal detection algorithm based on stochastic resonance energy detection should have the same constant false alarm probability as the conventional single-stage energy detector. The false alarm probability of a conventional single-stage energy detector can be calculated as

$$P_f = P(Tr \geq \lambda_{ED} | H_0) \tag{9}$$

λ_{ED} is the decision threshold of the conventional single-stage energy detection method. The stochastic resonance double threshold signal detection algorithm false alarm probability can be expressed as

$$\begin{aligned} P_f^* &= P(Tr^* \geq \lambda_2 | H_0) \\ &\quad + P(Tr_{SR} \geq \lambda_{SR} | \lambda_1 \leq Tr^* < \lambda_2, H_0) \times P(\lambda_1 \leq Tr^* < \lambda_2 | H_0) \end{aligned} \tag{10}$$

λ_{SR} is the decision threshold of the second-step perceptual stochastic resonance energy detection method.

Therefore, according to the Newman-Pearson criterion $P_f = P_f^*$

$$\begin{aligned} P(Tr \geq \lambda_{ED} | H_0) &= P(Tr^* \geq \lambda_2 | H_0) \\ &\quad + P(Tr_{SR} \geq \lambda_{SR} | \lambda_1 \leq Tr^* < \lambda_2, H_0) \cdot P(\lambda_1 \leq Tr^* < \lambda_2 | H_0) \end{aligned} \tag{11}$$

Depending on the characteristics of the stochastic resonance system, it can enhance other user signals input by the system when the conditions for generating stochastic resonance are met. Therefore, when other user signals are present, the user can obtain an enhanced received signal by stochastic resonance processing. However, when other user signals are not present, the stochastic resonance system will not function. Therefore, when $\lambda_2 \leq \lambda_{ED}$, under the H_0 condition, if the statistics of the first-stage sensing stage is less than λ_2, the statistics of the second-step sensing stage will not exceed λ_{SR}, because the Newman-Pearson criterion needs to maintain the same constant virtual alarm probability. This means that when $\lambda_2 \leq \lambda_{ED}$, there is

$$P(Tr_{SR} \geq \lambda_{SR} | \lambda_1 \leq Tr^* < \lambda_2, H_0) = 0 \tag{12}$$

Thus, the Eqs. (4–9) can be simplified to

$$P(Tr \geq \lambda_{ED} | H_0) = P(Tr^* \geq \lambda_2 | H_0) \tag{13}$$

In the actual perception process, the statistic Tr and Tr* expressions are the same, so if and only if $\lambda_2 = \lambda_{ED}$, the above equation holds.

When $\lambda_2 > \lambda_{ED}$, P_f^* can be further expressed as

$$\begin{aligned} P_f^* &= P(Tr^* \geq \lambda_{ED} | H_0) - P(\lambda_{ED} \leq Tr^* < \lambda_2, H_0) \\ &\quad + P(Tr_{SR} \geq \lambda_{SR} | \lambda_1 \leq Tr^* < \lambda_{ED}, H_0) \cdot P(\lambda_1 \leq Tr^* < \lambda_{ED} | H_0) \\ &\quad + P(Tr_{SR} \geq \lambda_{SR} | \lambda_{ED} \leq Tr^* < \lambda_2, H_0) \cdot P(\lambda_{ED} \leq Tr^* < \lambda_2 | H_0) \end{aligned} \tag{14}$$

Similarly, due to the Newman-Pearson criterion $P_f = P_f^*$, $P(Tr_{SR} \geq \lambda_{SR} | \lambda_1 \leq Tr^* < \lambda_{ED}, H_0) = 0$, the statistics Tr and Tr* expressions are the same (10), so

$$P(\lambda_{ED} \leq Tr^* < \lambda_2, H_0) = P(Tr_{SR} \geq \lambda_{SR} | \lambda_{ED} \leq Tr^* < \lambda_2, H_0) \times P(\lambda_{ED} \leq Tr^* < \lambda_2 | H_0) \tag{15}$$

According to the stochastic resonance linear response theory and the Newman-Pearson criterion, we can get $P(Tr_{SR} \geq \lambda_{SR} | \lambda_{ED} \leq Tr^* < \lambda_2, H_0) = 1$. So the above formula is always established. That is, when $\lambda_2 \geq \lambda_{ED}$, $P_f = P_f^*$ is always established. Since the upper threshold λ_2 is larger, the probability of performing the second step of perception is greater. Therefore, in order to minimize the computational complexity and ensure that the stochastic resonance system processes the weak signal, we select the upper threshold as $\lambda_2 = \lambda_{ED}$.

(2) Detection probability

According to the thresholds λ_1 and λ_2 determined in the previous section, the detection probability P_d^* of the two-step energy detection signal detection algorithm based on the stochastic resonance double threshold can be calculated as

$$P_d^* = P(Tr^* \geq \lambda_2 | H_1) + P(Tr_{SR} \geq \lambda_{SR} | \lambda_1 \leq Tr^* < \lambda_2, H_1) \cdot P(\lambda_1 \leq Tr^* < \lambda_2 | H_1) \tag{16}$$

In order to compare with the performance of stochastic resonance energy detection, we will explore the user detection probability using stochastic resonance energy detection, which can be expressed as

$$P_d = P(Tr_{SR} \geq \lambda_{SR} | H_1) \tag{17}$$

Using the full probability formula, we can get

$$\begin{aligned} P_d = {} & P(Tr_{SR} \geq \lambda_{SR} | Tr < \lambda_1, H_1) P(Tr < \lambda_1 | H_1) \\ & + P(Tr_{SR} \geq \lambda_{SR} | \lambda_1 \leq Tr < \lambda_2, H_1) P(\lambda_1 \leq Tr < \lambda_2 | H_1) \\ & + P(Tr_{SR} \geq \lambda_{SR} | Tr > \lambda_2, H_1) \cdot P(Tr > \lambda_2 | H_1) \end{aligned} \tag{18}$$

Because $\lambda_1 = \inf(\mathrm{Tr}^* : Tr_{SR} \geq \lambda_{SR})$, $P(Tr_{SR} \geq \lambda_{SR} | Tr < \lambda_1, H_1) = 0$. According to the rules selected above, in the presence of other users, if the stochastic resonance system works normally, when $Tr \geq \lambda_2$, there is naturally $Tr_{SR} \geq \lambda_{SR}$, so

$$\begin{aligned} P_d = {} & P(Tr_{SR} \geq \lambda_{SR} | \lambda_1 \leq Tr < \lambda_2, H_1) P(\lambda_1 \leq Tr < \lambda_2 | H_1) \\ & + P(Tr > \lambda_2 | H_1) \end{aligned} \tag{19}$$

Comparing (16) and (19), since the stochastic resonance double threshold two step detection algorithm and the stochastic resonance energy detection statistic are the same, both methods have the same detection probability.

The reference paper [11] and [12] proposed and discussed the compromise optimization of satellite communication network sensing and throughput. The perceptual time in a frame of user is obtained by maximizing the throughput of the satellite communication network, so

$$\begin{aligned} &\max_{ts} R(\tau_s) = \frac{T_f - \tau_s}{T_f}\left[C_0 \mathrm{P}(\mathrm{H}_0)(1 - \mathrm{P}_f(\tau_s)) + C_1 \mathrm{P}(\mathrm{H}_1)(1 - \mathrm{P}_d(\tau_s)\right] \\ &\text{s.t.} \quad P_d(\tau_s) > \overline{P_d} \end{aligned} \tag{20}$$

Among, τ_s is sensing time, Tf is MAC frame length, C_0 represents the throughput of authorized users is not occupy the channel, C1 represents the throughput of authorized users is occupy the channel, $P_d(\tau_s)$ is the detection probability, $P_f(\tau_s)$ is the false alarm probability, $\overline{P_d}$ is the target detection probability required by the PU.

In fact, since the occupancy rate of the PU to the target frequency band is no more than 0.3, the maximum satellite communication network throughput R can be equivalent to the maximization function $R_0 = C_0 P(H_0)(1 - \tau/T)(1 - P_f(\tau))$. Among the new Algorithm, $\lambda_1 \leq Tr^* < \lambda_2$, so P can be written as:

$$\mathrm{P}_1 = P(\lambda_1 \leq Tr^* < \lambda_2 / H_0) + P(\lambda_1 \leq Tr^* < \lambda_2 / H_1) \tag{21}$$

In this paper, the average sensing time required: $\tau_{T-SR} = \tau_1 + P\tau_2$, so τ_1 and τ_2 can be obtained by optimizing the throughput in the algorithm. The Throughput optimization problem of the double-threshold signal detection algorithm based on stochastic resonance technology can be described as:

$$\begin{aligned} &\max_{\tau_1,\tau_2} \ \mathrm{C}_0\mathrm{P}(\mathrm{H}_0)(1 - \frac{(\tau_1 + P_1\tau_2)}{T})(1 - \mathrm{P}_{F\_SR}) \\ &\text{s.t.} \ \tau_1 + \tau_2 \leq T \end{aligned} \tag{22}$$

To simplify the analysis, it is assumed that additive channel noise $n(t)$ fully meets the requirements for noise when stochastic resonance system synergizes. In other words, the input noise power is 0, so P_{F_SR} can be written as:

$$P_{F\_SR} = Q(1 + \frac{1}{\eta})Q^{-1}(\bar{P}_{D\_SR}) + \frac{1}{\eta}\sqrt{f_s(\tau_1 + \tau_2)/2} \tag{23}$$

Among, $\bar{P}_{D\_SR}$ is the target detection probability given to ensure the communication quality of PU, the formula (22) Can be further expressed as:

$$\begin{aligned} &\max_{\tau_1,\tau_2} \ \mathrm{C}_0\mathrm{P}(\mathrm{H}_0)(1 - \frac{(\tau_1 + P_1\tau_2)}{T})(1 - Q(1 + \frac{1}{\eta})Q^{-1}(\bar{P}_{D\_SR}) + \frac{1}{\eta}\sqrt{f_s(\tau_1 + \tau_2)/2}) \\ &\text{s.t.} \ \tau_1 + \tau_2 \leq T \end{aligned} \tag{24}$$

When the perceived duration τ_1 or τ_2 is fixed, the optimization objective function is simplified into a convex optimization problem. For the one-dimensional convex optimization problem, the conventional efficient method can be used to solve the optimization problem.

4 Simulation Results and Analysis

The above theoretical derivation and analysis are verified by simulation. In order to improve the detection performance, a typical bistable system is used in the simulation. Its potential function is $V(x) = -\frac{1}{2}x^2 + \frac{1}{4}x^4$, other user signals use BPSK signals with a frequency of 10 kHz. The signal received by the user is a signal that superimposes additive white Gaussian noise after the other user signals and other BPSK interference signals pass through the flat slow fading channel.

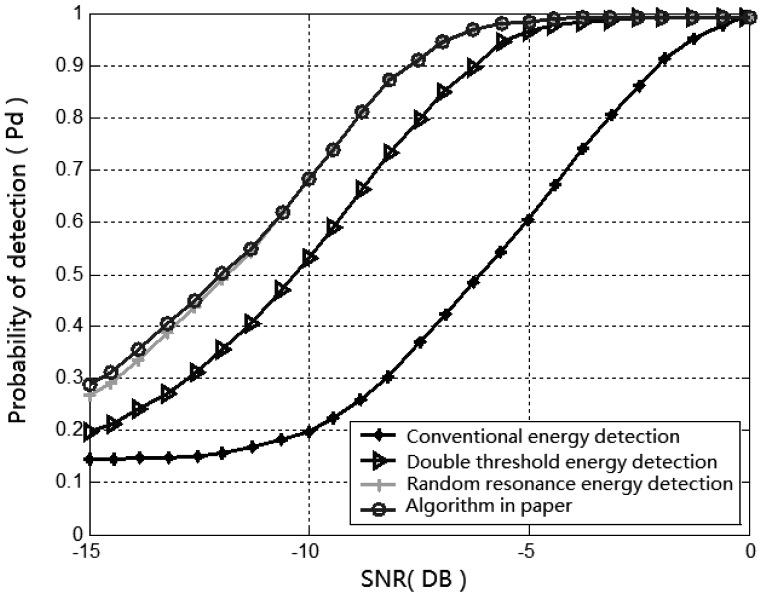

Fig. 5. Signal-to-noise ratio and the detection probability curve

Figure 5 shows the signal detection algorithm for conventional energy detection, double threshold energy detection, stochastic resonance energy detection and stochastic resonance double-threshold two-step energy detection under different conditions of sample number N = 1000 and false alarm probability of 0.05. Comparison of simulation probability under noise ratio conditions; Fig. 6 shows a comparison of receiver operating characteristics at a signal-to-noise ratio of −10 dB. It can be seen from the figure that compared with the conventional energy detection, based on the stochastic resonance energy detection algorithm, the detection probability is significantly improved under low noise conditions, the signal detection algorithm based on stochastic resonance energy detection and stochastic resonance double threshold two step energy detection is superior to conventional energy detection and dual-threshold energy detection algorithms. From the simulation diagram, we also found that the stochastic resonance energy detection and the double-threshold energy signal detection algorithms based on stochastic resonance have the same detection performance regardless of the conditions, which also verifies the correctness of the theoretical derivation.

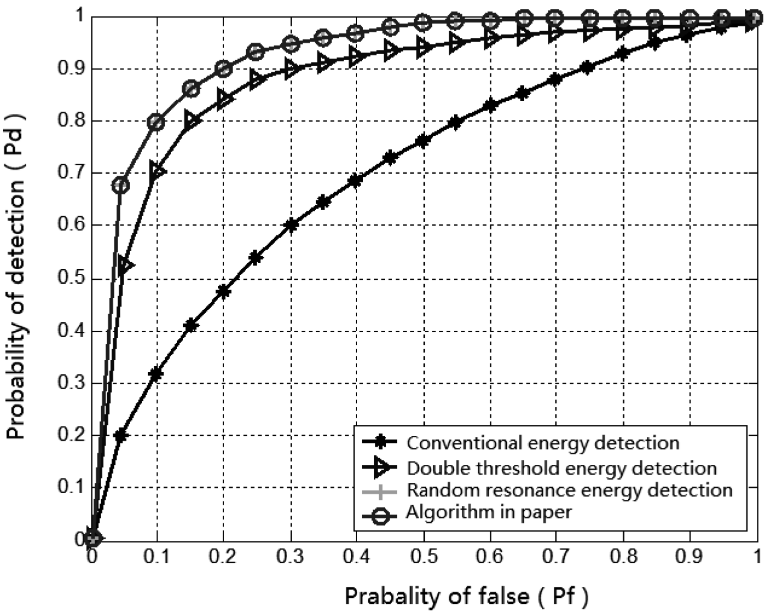

Fig. 6. Detection performance curve comparison chart

Now let's verify the throughput optimization problem. Take the MAC frame length as 60 ms. The sampling frequency of BPSK signal is 10 kHz. Assuming that P (H_0) = P(H_1) = 0.5, $\bar{P}_d = 0.9$. The maximum reachable throughput under different τ_1 and all possible τ_2 is shown in Fig. 7.

It can be seen that under different SNR, the curve of its maximum achievable throughput is convex. So, under all possible conditions, it can always find one that enables the maximum through put to be reached. When the SNR is at −5 dB, it reaches the maximum value τ_1 = 8 ms, which is 2.2790. When the SNR is −5.2 dB, it reaches the maximum value τ_1 = 10 ms, which is 2.0839.

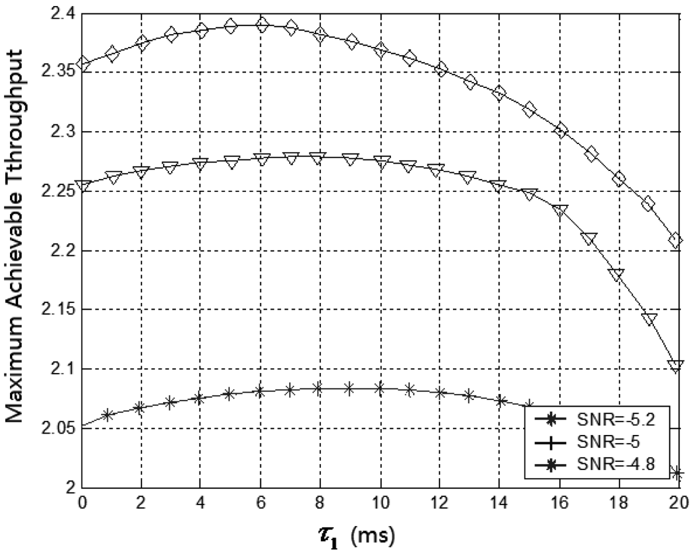

Fig. 7. Relation with maximum throughput curve and τ_1 under different SNR

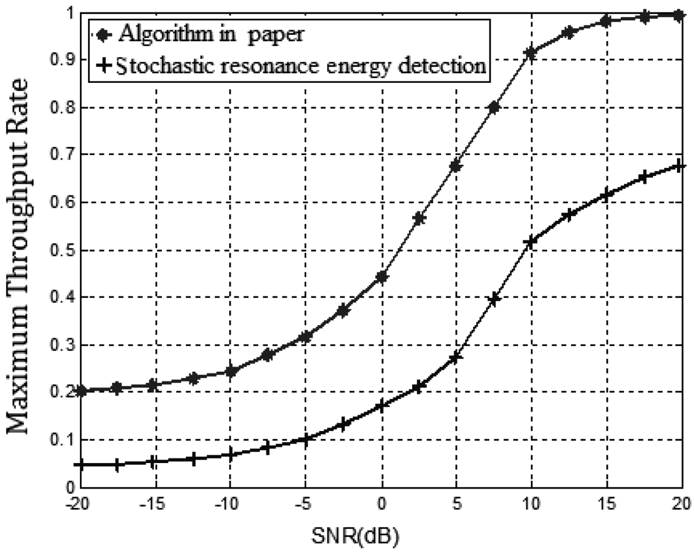

Fig. 8. The contrast of the Maximum throughput rate under different SNR

Furthermore, the maximum throughput rate and optimal average perceived time of the two algorithms are simulated under different signal-to-noise ratios. In the simulation condition, the SNR under H_0 condition is set to 20 dB, under H_1 condition is −10 dB, the MAC frame length is 50 ms, and P(H0) = 0.7, the detection probability is set to 0.9.

Figure 8 shows the comparison of maximum reachable satellite communication network throughput rate under different signal-to-noise ratios between the double-threshold signal detection algorithm based on stochastic resonance and the energy detection algorithm based on stochastic resonance. It can be seen from the simulation figure that compared with the energy detection method based on stochastic resonance, double-threshold signal detection algorithm based on stochastic resonance can achieve a large network throughput with less perception time.

5 Conclusion

In this paper, the satellite communication is performed under the condition of low SNR. According to the characteristics of the stochastic resonance system with enhanced other user signals received by the user, a double threshold signal detection algorithm based on stochastic resonance is proposed. And two decision thresholds are derived to determine the double threshold perception algorithm. When the access user needs to perform random resonance processing on the normal user signal received by the user, the effective detection of the small signal with low SNR condition is realized. The simulation results show that the detection performance is effectively improved. This method has higher signal detection efficiency, better universal applicability and throughput, so the double-threshold signal detection algorithm based on stochastic resonance improves the satellite communication network performance effectively.

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References

1. He, D., He, C., Jiang, L.: Spectrum sensing approach based on optimal stochastic resonance technique under color noise background in cognitive radio networks. In: 2010 IEEE International Conference on Communications Workshops (ICC), pp. 1–4 (2010)
2. Lin, Y., He, C., Jiang, L.: A cyclostationary-based spectrum sensing method using stochastic resonance in cognitive radio. In: IEEE International Conference on Communications Workshops (ICC), pp. 1–5 (2010)
3. Chen, H., Varshney, P.K.: Theory of the stochastic resonance effect in signal detection—part II: variable detectors. IEEE Trans. Sig. Process. **56**(10), 5031–5041 (2008)
4. He, D., Lin, Y.P., He, C.: A novel spectrum sensing technique in cognitive radio based on stochastic resonance. IEEE Trans. Veh. Technol. **59**(4), 1680–1688 (2010)
5. Jia, M., Gu, X., Guo, Q., Xiang, W., Zhang, N.: Broadband hybrid satellite-terrestrial communication systems based on cognitive radio toward 5G. IEEE Wirel. Commun. **23**(6), 96–106 (2016)
6. Jia, M., Liu, X., Gu, X., Guo, Q.: Joint cooperative spectrum sensing and channel selection optimization for satellite communication systems based on cognitive radio. Int. J. Satell. Commun. Netw. **35**(2), 139–150 (2017)

7. Jiang, X.L., Gu, X.M.: Double threshold collaborative spectrum sensing algorithm based on energy detection. J. Hei LongJiang Univ. Sci. Technol. 553–556 (2016)
8. Chen, H., Varshney, P.K., Kay, S.M.: Theory of the stochastic resonance effect in signal detection: part I—fixed detectors. IEEE Trans. Sig. Process. **55**(7), 3172–3184 (2007)
9. Kawaguchi, M., Mino, H., Momose, K., Durand, D.M.: Stochastic resonance with a mixture of sub-and supra-threshold stimuli in a population of neuron models. In: IEEE International Conference on Engineering in Medicine and Biology Society (EMBC), pp. 7328–7331 (2011)
10. Wu, J.: A cooperative double-threshold energy detection algorithm in cognitive radio systems. In: IEEE International Conference on Wireless Communications Networking and Mobile Computing (2009)
11. Liang, Y.C., Zeng, Y.: Sensing-throughput tradeoff for cognitive radio networks. IEEE Trans. Wirel. Commun. **7**(4), 1326–1337 (2008)
12. Peh, E.C.Y., Liang, Y.C., Guan, Y.L.: Optimization of cooperative sensing in cognitive radio networks: a sensing-throughput tradeoff view. IEEE Trans. Veh. Technol. **58**(9), 5294–5299 (2009)