International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 1198-1208

https://doi.org/10.70517/ijhsa464112

# Research on an improved energy detector with adaptive double threshold

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**Abstract** In environments characterized by low signal-to-noise ratios (SNR),the traditional double-threshold algorithm applies a fixed threshold, leading to less than ideal detection results. In order to enhance the detection probability while simultaneously minimizing the false alarm probability, an improved energy detector, equipped with an adaptive double threshold (IED_ADT), has been employed. This advanced mechanism allows for dynamic threshold adjustments, optimizing performance under various conditions. By utilizing an adaptive approach, the IED_ADT effectively reduces the likelihood of false alarms, thus ensuring more accurate detection.The detector adjusts the decision threshold based on the Neyman-Pearson criterion, correlates the current decision result with previous and subsequent moments, and then derives a detection probability formula for an improved adaptive strategy under a single-user. Subsequently, it further fuses the decision information from each node to obtain the cooperative spectrum sensing result. Theoretical analysis, accompanied by simulation results, has shown that the IED_ADT scheme, notably, offers superior performance compared to conventional detection algorithms. This is particularly evident in the detection probability (Pd), especially when the signal-to-noise ratio (SNR) is fixed at -8 dB. At this SNR level, the IED_ADT method, which incorporates an adaptive double threshold, significantly enhances detection accuracy, far exceeding the capabilities of traditional algorithms.The optimal improved detection power exponent for this scheme is found to be 2.5.The proposed adaptive double-threshold detection algorithm presented in this paper demonstrates a 72.6% improvement in system sensing performance for a single user, in contrast to the conventional double-threshold detection algorithm under enhanced energy detection conditions. In low Signal-to-Noise Ratio environments, ranging from -5 dB to 2 dB, the proposed adaptive double-threshold detection algorithm significantly outperforms traditional detection methods in terms of detection performance. Similarly, when SNR is below 0 dB and multi-user collaborative spectrum sensing is applied, the fusion decision strategy notably enhances the performance of the IED_ADT detector.No matter whether the "AND" criterion or the "OR" criterion is adopted by the fusion center, the system's detection performance improves by over 50%.

**Index Terms** Cognitive radio, Spectrum sensing, Improved energy detection, Adaptive double threshold

## I. Introduction

As wireless communication technology advances rapidly, the need for spectrum resources has increased substantially. Research shows that the usage rate of the licensed frequency band varies from 15% to 85% [1]-[3]. To optimize resource usage, Dr. Joseph Mitola initially introduced the concept of the Cognition Cycle in IEEE Personal Communications [4], [5].Spectrum sensing serves as a core technology within cognitive radio systems, with energy detection being a dependable method for detecting uncorrelated signals in spectrum detection, which has the characteristics of no prior information and fast sensing speed, but is easily affected by noise uncertainty [6]-[8]. The research on the energy detec-tion algorithm is mature in China and abroad. Ref. [9] analyzes the interference factors affecting the primary receiver, taking into account different information arrival rates and capacity sizes in the environment. The throughput scaling laws for three distinct cognitive networks are established, with the aim of enhancing cognitive network efficiency and achieving superior communication performance. In Ref. [10], Mokhtar et al. propose a distributed framework for processing and fusing sensing information. The study presents an innovative distributed detection method, featuring an adaptive threshold mechanism tailored for Rayleigh fading environments, with the goal of controlling the false alarm probability. By optimizing this detection method, the system's performance in varying conditions is significantly improved.This approach enhances both sensing reliability and efficiency, increasing the sensing sensitivity to 0.95 in such conditions. Kaleem et al.proposed a SPU transmission model based on CSS, developed an energy detection technique, and reprocessed a hybrid handoff scheme based on DSA in Ref.[11]. This model not only reduces energy consumption but also enhances throughput and sensing efficiency, demonstrating exceptional performance in improving energy efficiency. Ref. [12] presents a

HD, crafted to comply with the IEEE WRAN 802.22 standard, which facilitates the identification of unoccupied TV spectrum. In conditions of low SNR, specifically at -20 dB, the CSS environment exhibited optimal performance, achieving peak levels in both detection probability and false alarm probability. The system, when operating under such challenging SNR levels, demonstrated its capability to maintain a high detection rate while effectively minimizing the occurrence of false alarms. The 5G era has arrived, and spectrum sensing technology also plays an important role. BALACHANDER et al. examines NOMA communication technology and introduces an innovative approach to cooperative spectrum sensing in paper [13]. In this approach, secondary users (SUs) transmit data simultaneously on the licensed spectrum bands of primary users (PUs), ensuring that interference levels with the PUs remain below a predefined threshold. The method carefully controls the interference caused by SUs, maintaining it within acceptable limits to avoid disrupting the communication of primary users. By adhering to this threshold, the system effectively balances the need for efficient spectrum sharing while safeguarding the integrity of the primary users' transmissions.Ref. [14] emphasizes a notable enhancement in SE, exceeding 50%, across different configurations in 5G networks. This improvement is observed in setups such as SISO, 64×64 MIMO, and 128×128 massive MIMO. This is accomplished by permitting users to access CCRN channels through a C-CH, while the CCRN fulfills channel requirements via a D-CH. By utilizing the C-CH for initial access and the D-CH for channel allocation, the system efficiently manages spectrum resources, ensuring that users' demands are met without causing interference. In Ref. [15], 5G wireless technology is leveraged to enhance both the efficiency and accuracy of IoT networks. The study employs the Offset Quadrature Amplitude Modulation Universal Filtered Multi-Carrier Non-Orthogonal Multiple Access (OQAM/UFMC/NOMA) method, optimizing CSS within CRN. Furthermore, the EEAPF algorithm is applied, significantly reducing the PAPR. This combined approach ensures improved performance in IoT networks by addressing both spectrum sensing and power efficiency challenges, particularly at a high level of precision.

The double threshold energy detection technique has been demonstrated to be highly effective in reducing the adverse effects of noise uncertainty. By employing this method, one can significantly diminish the influence of random noise, which otherwise complicates accurate detection.Ref.[16] proposes a two-bit quantization algorithm based on multi-energy detectors and adaptive double thresholds to judge the signals between double thresholds to improve the detection performance. Ref. [17] introduces a cooperative spectrum sensing approach utilizing dynamic dual thresholds, designed to address threshold mismatches in energy detectors caused by noise power uncertainty. This method features a dynamic adjustment mechanism for dual thresholds that effectively mitigates the impact of noise uncertainty. Ref. [18] examines physical layer security in cognitive buffered relay networks, investigating how to optimize link selection to improve confidentiality in Nakagami-m fading channels. The research presents a closed-form expression for the calculation of the SOP, which confirms that the performance related to confidentiality undergoes a significant enhancement as the Nakagami parameter, denoted by m, increases. This expression provides a precise mathematical framework for evaluating how the confidentiality performance—characterized by the security outage probability—improves notably with an elevation in the Nakagami parameter value. It is evident that as m rises, there is a discernible augmentation in the level of confidentiality achieved, underscoring the effectiveness of the parameter in improving the security metrics.Ref. [19] investigates how sample size influences spectrum sensing performance and introduces two innovative approaches: optimal sample size $N*$ and neural network (NN) optimization, aimed at enhancing energy detection performance with single and double thresholds. Using an unbiased estimation of noise variance with a Gaussian distribution, a new and realistic noise uncertainty (NU) model is applied. Ref. [20] establishes the optimal global detection performance across different decision rules and presents an empirical SNRw algorithm. This algorithm aids in the calculation of SNRw for any detector in both nCSS and CSS contexts.

This paper derives the optimal global probabilities for detection and false alarms by employing a dual-threshold approach within an enhanced energy detection scheme. This strategy aims to optimize both local and cooperative spectrum sensing performance. Compared with the previous literature such as [19], which did not focus much on the sampling value and set it to 100 to ensure the feasibility of the central limit theorem, the innovation of this paper lies in correlating the detection probability values obtained from the adaptive double-threshold strategy with the values at the preceding and following moments, thereby achieving better system performance. The structure of the remainder of this manuscript is structured as follows: Section 2 presents the spectrum sensing model utilized by the system.Section 3 presents the optimized adaptive dual-threshold energy detection strategy. Section 4 derives the global probability under the hard fusion decision rule is selected as the FC. Section 5 elaborates on the experimental findings and ensuing discussions, elucidating that the proposed methodology exhibits superior performance compared to the conventional single-threshold energy detection algorithm regarding sensing efficacy. The detailed analysis within this section reveals that the novel approach, through its advanced mechanisms, surpasses the traditional method in terms of the effectiveness of detection. The comparison, therefore, underscores a marked enhancement in sensing performance when employing the proposed technique as opposed to its traditional counterpart. Section 6 summarizes the conclusions of this scholarly work.

## II. System model

The energy detection algorithm formulates a binary hypothesis in order to determine the presence or absence of the PU within the current spectrum. Through this approach, the algorithm assesses whether the primary user is detected or not, based on the established hypothesis. By employing this binary framework, the algorithm effectively discerns the spectral occupancy status of the primary user, thereby facilitating accurate detection and analysis within the given spectrum.The energy statistics collected by a single CU are modeled as follows.

$$y_k(n) = w_k(n),\ H_0\text{:PUabsent} \tag{1}$$

$$y_k(n) = s_k(n) + w_k(n),\ H_1\text{:PUpresent} \tag{2}$$

In this context, $k$ represents the $k$-th CU, with the maximum possible value being M. The variable $s_k(n)$ indicates the signal transmitted by users at the n-th sampling instance, where the maximum allowable value is N. Assuming the local sensing operations of each cognitive user are conducted independently, the energy detection method is employed for decision-making purposes. In this scenario, the method facilitates the determination of spectral occupancy by utilizing individual sensing processes that function autonomously.

It is postulated that the stochastic signal conforms to a Gaussian distribution, characterized by a mean of zero and a variance denoted by $\sigma_s^2$. Within this framework, it is assumed that the signal's behavior adheres to the statistical properties of a Gaussian distribution, where the mean is specifically zero and the variance is symbolized by the value $\sigma_s^2$. Additionally, $w_k(n)$ represents Gaussian noise, which also has a mean of zero and a variance designated as $\sigma^2$. Furthermore, it is asserted that $s_k(n)$ and $w_k(n)$ are independent variables. The formulas expressing the relationship between these two distributions can be respectively denoted as $s_k(n) \sim N(0, \sigma_s^2)$ and $w_k(n) \sim N(0, \sigma^2)$.

## III. Local spectrum sensing strategy

### *III. A. Improved energy detection*

The IED algorithm can also be expressed as a binary hypothesis process, where the input time domain signal $y_k(n)$, after filtering and A/D conversion, the sampled values are squared and then summed to produce the detection statistics. These statistics are then evaluated against a threshold value to elucidate if the PU is occupying the current spectrum.

Figure 1 illustrates the diagram of the detection algorithm.

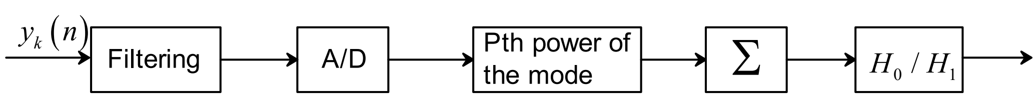


Figure 1: The detection algorithm diagram

The improved energy statistics received from the k-th user can be expressed as

$$Y_k = \frac{1}{N}\sum_{n=1}^{N} |y_k(n)|^p,\ p > 0 \tag{3}$$

According to Y. Chen in [21] and I. S. Gradshteyn et al. in [22], the average and variance of the statistics $Y_k$ under $H_0$ are

$$E(Y_k | H_0) = \frac{2^{p/2}\Gamma\left(\frac{1+p}{2}\right)}{\sqrt{\pi}} \tag{4}$$

$$Var(Y_k | H_0) = \frac{2^p}{n}\left[\frac{\Gamma\left(\frac{1+2p}{2}\right)}{\sqrt{\pi}} - \frac{\Gamma^2\left(\frac{1+p}{2}\right)}{\pi}\right] \tag{5}$$

Among them, $\Gamma(\cdot)$ refers to the full gamma function.

Under $H_1$ the average and variance of the statistics $Y_k$ are

$$E\left(Y_k|H_1\right)=E\left(Y_k|H_0\right)\left(\sqrt{1+\gamma}\right)^p \tag{6}$$

$$Var\left(Y_k|H_1\right)=Var\left(Y_k|H_0\right)\left(1+\gamma\right)^p \tag{7}$$

where, F. F. Digham et al. in [23] is represented as $\gamma=\frac{\sigma_s^2}{\sigma^2}$.

In alignment with the central limit theorem, the probability of a false alarm, represented as $P_f$, for the k-th CU is:

$$P_f=Q\left(\frac{\lambda-E\left(Y_k|H_0\right)}{\sqrt{Var\left(Y_k|H_0\right)}}\right) \tag{8}$$

$\lambda$ is the single decision threshold, $Q(\cdot)$ is the standard Gaussian function of the cumulative complementary functions.

The detection probability $P_d$ of each CU is as:

$$P_d=Q\left(\frac{\lambda-E\left(Y_k|H_1\right)}{\sqrt{Var\left(Y_k|H_1\right)}}\right) \tag{9}$$

The false dismissal probability $P_m$ is as follows:

$$P_m=1-P_d \tag{10}$$

### *III. B. Adaptive double threshold algorithm*

Figure 2 illustrates the core principle underlying the double threshold energy detection algorithm. This visual representation elucidates the foundational concept of the algorithm, which is designed to enhance detection accuracy by employing dual thresholds. The depiction in the figure provides a clear understanding of how the algorithm operates, detailing its operational framework and the rationale behind its use of two distinct thresholds to optimize performance in detecting signals amidst noise.

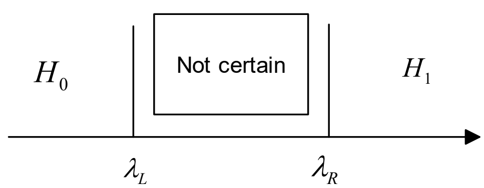


Figure 2: Double threshold energy detection model

It has two different decision thresholds $\lambda_L$ and $\lambda_R$, the detection statistics $T$ are obtained from known signals.

If $T>\lambda_R$, it is judged $H_1$ to be correct. At this time, there is an authorized user signal and the CU cannot use the current channel.

If $T<\lambda_L$, the judgment $H_0$ is correct, there is no authorized user signal at this time, and the CU uses the current channel.

If $\lambda_L<T<\lambda_R$, At this moment, it is not possible to determine whether an authorized user signal is present, and a new judgment is needed until a correct result appears.

$$Y_k=\begin{cases} H_0, T>\lambda_L \\ \text{Not certain}, \lambda_L<T<\lambda_R \\ H_1, T<\lambda_R \end{cases} \tag{11}$$

The adaptive threshold algorithm is adopted in this paper, and the concrete implementation is as follows: when it is between two thresholds, the last decision result is taken as the current decision result, and if it is also between two thresholds, the next decision result is taken as the current decision result.

Based on the Sun Mengwei et al. in [24], the noise is not ideal Gaussian white noise, but fluctuates continuously in a certain range. Assuming that the uncertainty of noise is a, the range of values is $1<a<\infty$, the estimated noise power is $\hat{\sigma}_w^2$, and the variation amplitude can be expressed by the uncertainty as follows, $\hat{\sigma}_w^2\in(\frac{\sigma_w^2}{a},a\sigma_w^2)$.

Setting parameter $\rho=\frac{\hat{\sigma}_w^{\,2}}{\sigma_w^{\,2}}$, referring to the traditional energy detection algorithm, using the Newman-Pearson criterion, setting the detection double threshold value is:

$$\lambda_L=[\sqrt{Var(Y_k \mid H_0)}Q^{-1}(P_f)+E(Y_k \mid H_0)]/\rho \tag{12}$$

$$\lambda_R=[\sqrt{Var(Y_k \mid H_0)}Q^{-1}(P_f)+E(Y_k \mid H_0)]\rho \tag{13}$$

According to the adaptive double threshold algorithm, $P_d$ is:

$$\begin{gathered} P_d=P\{Y_{k,now}>\lambda_R|H_1\}+P\{\lambda_L<Y_{k,now}<\lambda_R|H_1\}* \\ \left(P\{Y_{k,pre}>\lambda_R|H_1\}+P\{\lambda_L<Y_{k,pre}<\lambda_R|H_1\}*P\{Y_{k,aft}>\lambda_R|H_1\}\right) \end{gathered} \tag{14}$$

Where, the statistical values of the detection under this time $Y_{k,now}$, preceding and following moments $Y_{k,pre}$, $Y_{k,aft}$ are respectively. Combined with Eq.(9), the detection probability for the cognitive user (CU) can be calculated as follows:

$$\begin{gathered} P_d=Q\left(\frac{\lambda_R-E(Y_k \mid H_1)}{\sqrt{Var(Y_k \mid H_1)}}\right)* \\ \left\{\begin{array}{l} 1+Q\left(\frac{\lambda_L-E(Y_k \mid H_1)}{\sqrt{Var(Y_k \mid H_1)}}\right)-Q\left(\frac{\lambda_R-E(Y_k \mid H_1)}{\sqrt{Var(Y_k \mid H_1)}}\right)+ \\ \left[Q\left(\frac{\lambda_L-E(Y_k \mid H_1)}{\sqrt{Var(Y_k \mid H_1)}}\right)-Q\left(\frac{\lambda_R-E(Y_k \mid H_1)}{\sqrt{Var(Y_k \mid H_1)}}\right)\right]^2 \end{array}\right\} \end{gathered} \tag{15}$$

Similarly, Eq.(8) can be obtained as follows:

$$\begin{gathered} P_f=Q\left(\frac{\lambda_R-E(Y_k \mid H_0)}{\sqrt{Var(Y_k \mid H_0)}}\right)* \\ \left\{\begin{array}{l} 1+Q\left(\frac{\lambda_L-E(Y_k \mid H_0)}{\sqrt{Var(Y_k \mid H_0)}}\right)-Q\left(\frac{\lambda_R-E(Y_k \mid H_0)}{\sqrt{Var(Y_k \mid H_0)}}\right)+ \\ \left[Q\left(\frac{\lambda_L-E(Y_k \mid H_0)}{\sqrt{Var(Y_k \mid H_0)}}\right)-Q\left(\frac{\lambda_R-E(Y_k \mid H_0)}{\sqrt{Var(Y_k \mid H_0)}}\right)\right]^2 \end{array}\right\} \end{gathered} \tag{16}$$

## IV. Fusion strategy

In the mutually beneficial detection model, the fusion center utilizes a hard fusion approach, incorporating criteria such as AND, OR, and K rank. For the criterion of rank K , a voting threshold, denoted as K , is determined, wherein K is set to a value less than the aggregate number of CUs. In this context, the threshold K serves as a pivotal parameter, established to be below the total count of cognitive users, thus facilitating the decision-making process. The channel is deemed unoccupied if fewer than K users make $H_1$ decisions. When K is equal to 1, when K equals the total number of CUs, the criterion is AND. In contrast, if K is less than the total number of CUs, the criterion employed is OR.

The total false alarm probability $P_F$ and the detection probability $P_D$ for the fusion center (FC) are defined as follows:

$$P_F=\sum_{i=K}^{M}C_M^K P_f^{\,i}\left(1-P_f\right)^{M-i} \tag{17}$$

$$P_D=\sum_{i=K}^{M}C_M^K P_m^{\,M-i}\left(1-P_m\right)^{i} \tag{18}$$

## V. Numerical results and discussions

### *V. A. Description of experimental conditions and simulation process*

All simulations in this study are performed using MATLAB (version R2018a). To compare the different scenarios discussed earlier,ROC curves are utilized. The efficacy of an individual node user is evaluated within a Gaussian channel framework, under the assumption that the Gaussian noise adheres to a standard normal distribution characterized by a mean of 0 and a variance of 1. In this analysis, the performance is meticulously examined under the assumption that the noise adheres to a standard normal distribution, where the mean is precisely zero and the variance is consistently one. Additionally, the signal transmitted by the primary user at the n-th time instance is conceptualized as conforming to a normal distribution, distinguished by a mean of 0 and a variance of $\sigma_s^2$. Following the central limit theorem applied in Eq. (9), the number of sampling points n is established at 100. The noise uncertainty is assigned to 1.25, and the Monte Carlo simulation is conducted with a cycle value of 10,000.

To demonstrate the algorithm's effectiveness and account for variations among CU nodes, the working parameters of each CU node are assumed to be constant and same for a certain period of time. The adaptive double threshold algorithm flow chart is shown in Figure 3 in the case of a single node detection.

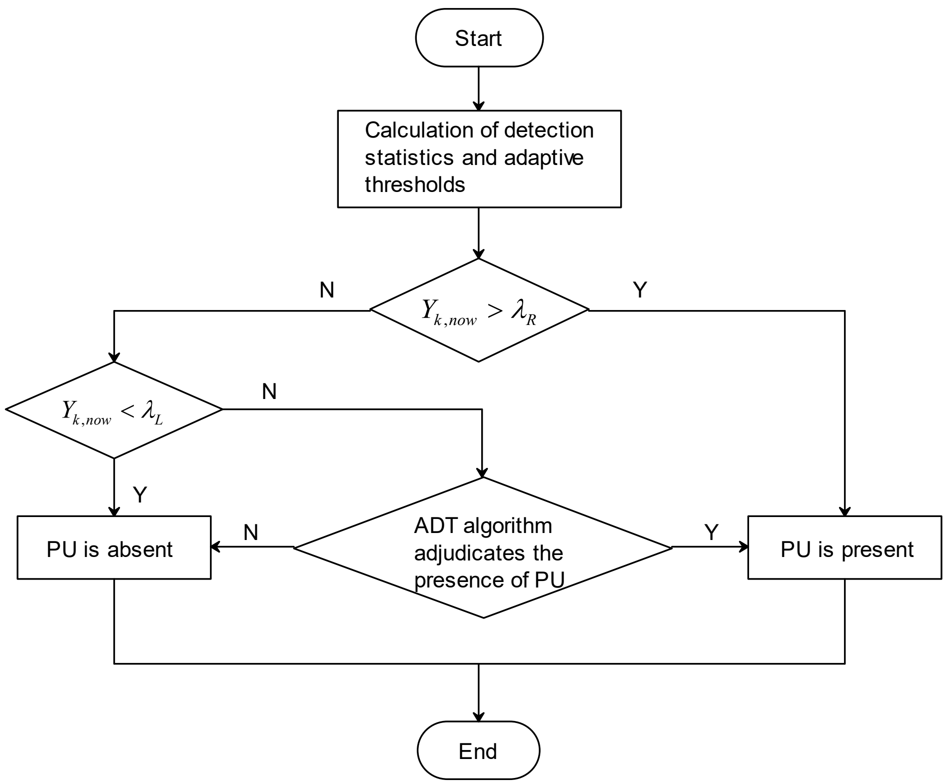


Figure 3: The adaptive double threshold algorithm flow chart

### *V. B. Single-node Spectrum Sensing*

Firstly, to assess the viability of the P-th energy detection method, figure 4 displays the detection probability curves of the system as the P-factor of the improved energy detector changes, across four scenarios with false alarm probabilities set at 0.01, 0.05, 0.3, and 0.5, respectively, while the system's SNR is fixed at -8 dB. It is evident that when the parameter P is less than 3, the theoretical results align closely with the simulation outcomes. This observation further substantiates the viability of the IED algorithm and confirms the accuracy of Equation (9). This conclusion is especially evident at the false alarm probability is 0.01 and $P_f$ in the other three cases, the theoretical value and the simulation value deviated greatly. Consequently, the probability of false alarms within the system is established at 0.01 for the purposes of this research.

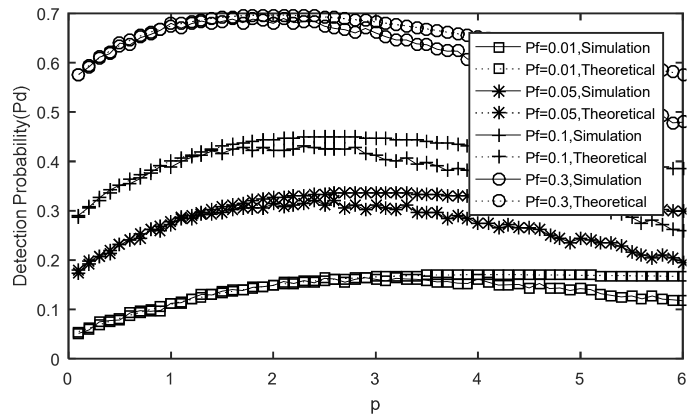


Figure 4: Pd vs. p of the improved energy detector

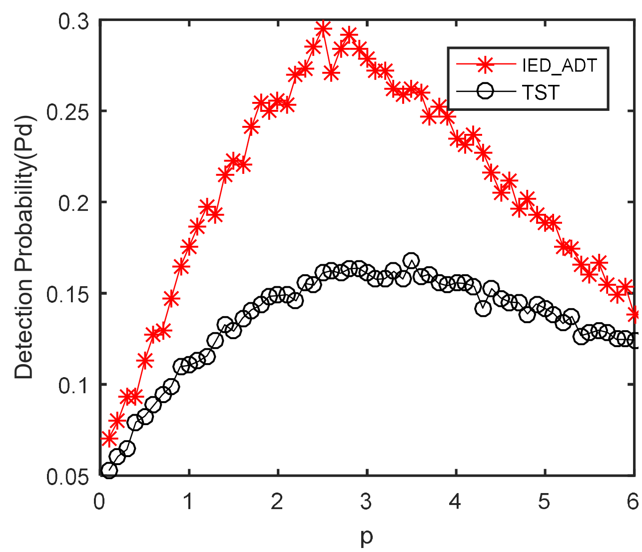


Figure 5: The detection probability with the changing of detector factor P

Figure 5 illustrates the curve depicting the nexus between the detection probability $P_d$ and the detector factor P, with the false alarm probability $P_f$ fixed at 0.01 and the SNR set to -8 dB. The P value ranges from 0.1 to 6. It is evident that the optimal value for maximizing the improved detection probability, which corresponds to the peak detection probability, is 2.5. Notably, this optimal value is not equal to 2,which verifies the viability of the IED and the IED_ADT scheme out-performs distinctly. It can be clearly compared that the detection probability of the adaptive double threshold algorithm can achieve better detection than that of the traditional single threshold (TST) algorithm. The more detailed values taken in Figure 5 are shown in Table 1, the best detection probability value obtained by the improved adaptive algorithm is 0.2906, while the detection probability of traditional single threshold is 0.1684. The IED_ADT strategy results in a profoundly improved systematic spectrum sensing performance, with a 72.6% increase in checking performance.

Table 1: The partial detection probability of Figure 5

| P | $P_d$ (IED_ADT) | $P_d$ (TST) |
|---|---|---|
| 1.8 | 0.2407 | 0.1377 |
| 1.9 | 0.2552 | 0.1469 |
| 2 | 0.2459 | 0.1470 |
| 2.1 | 0.2593 | 0.1510 |
| 2.2 | 0.2770 | 0.1447 |
| 2.3 | 0.2791 | 0.1520 |
| 2.4 | 0.2784 | 0.1591 |

| | | |
|---|---|---|
| 2.5 | 0.2906 | 0.1576 |
| 2.6 | 0.2796 | 0.1579 |
| 2.7 | 0.2840 | 0.1588 |
| 2.8 | 0.2849 | 0.1540 |
| 2.9 | 0.2721 | 0.1628 |
| 3 | 0.2801 | 0.1684 |
| 3.1 | 0.2732 | 0.1614 |
| 3.2 | 0.2731 | 0.1615 |

Figure 6 shows the influence curve of system perception performance on the change of SNR under the optimal detection power exponent of 2.5 and the selected false alarm probability of 0.01, the change range of SNR is -10dB to 10dB. When the SNR is greater than -10dB and less than 2dB, comparing the TDT algorithm and the TST algorithm, the IED_ADT adaptive has optimal detection performance obviously. The three algorithms have little difference and the curves are consistent when SNR is greater than 2dB.

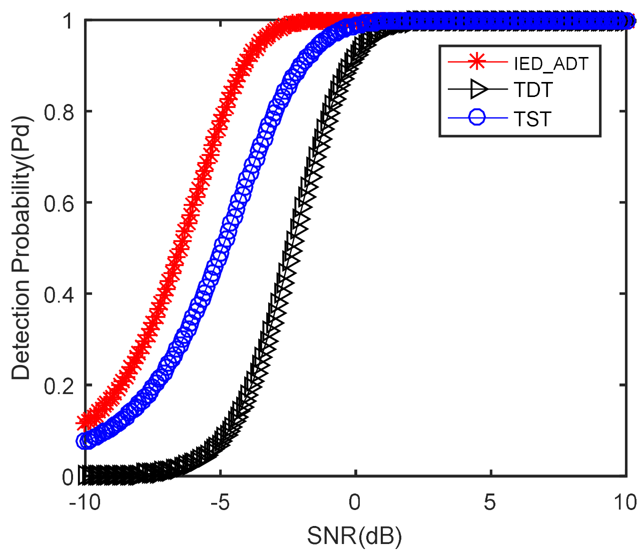


Figure 6: Comparison of two methods with an increasing number of SNR

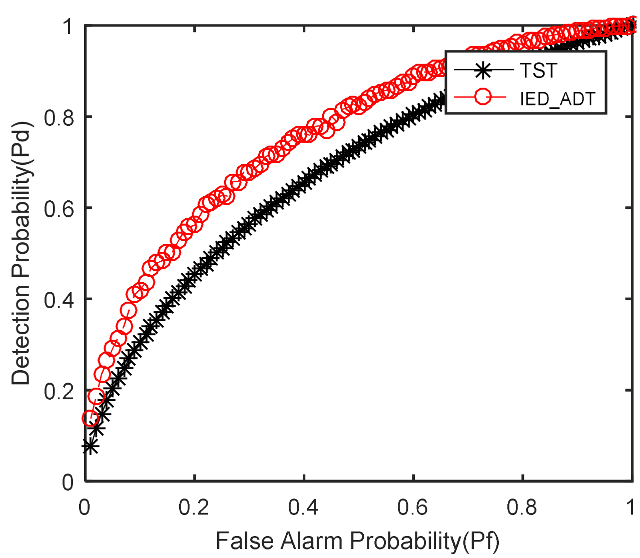


Figure 7: ROC curves for SNR is -8dB and the P paramete is 2.5

Figure 7 displays the ROC curve for a sample size of 100, with a SNR of -10 dB and a P parameter value of 2.5 for the IED. The comparison between the detection outcomes of the adaptive double threshold algorithm and the single threshold methodology persistently underscores the enhanced efficacy of the former. Analyzing the results reveals that the adaptive double threshold approach consistently exhibits a markedly superior performance when juxtaposed with the single threshold technique.

### *V. C. Multi-user Collaborative Spectrum Sensing*

The previous section analyzed the simulation results for single-node spectrum sensing. The following analysis examines the sensing performance of the system under a fusion strategy. In this analysis, the number of secondary users (M) is fixed at 10, with P set to 2.5 and the false alarm probability at 0.01. The performance assessment of the IED_ADT algorithm, compared to the traditional double threshold algorithm, is conducted under the "AND" criterion employed at the fusion center, as depicted in Figure 8. It shows that the former has a better effect and the higher detection probability when SNR greater than 0dB. For example, when the SNR is -2 dB, the detection probability achieved with the adaptive double-threshold algorithm is 0.8526, while the detection probability obtained by traditional detection methods is 0.0447, indicating the performance improvement exceeds 50%.

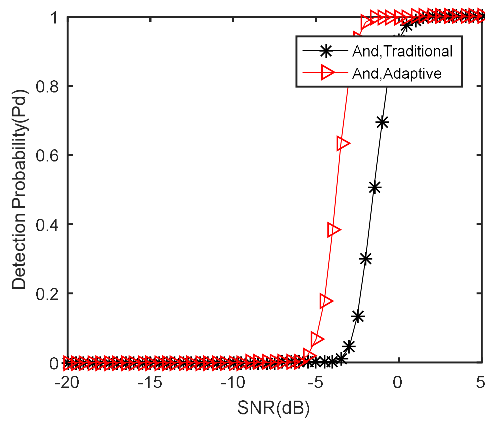


Figure 8: Pd vs. SNR under the "AND" criterion

The algorithm introduced in this study surpasses the traditional double-threshold detection method by achieving a higher detection probability and maintaining a lower false alarm probability, assuming the false alarm probability remains constant. Figure 9 shows a performance comparison between the adaptive improved algorithm and the conventional detection algorithm, utilizing the "OR" criterion for selecting the fusion center (FC).The proposed algorithm demonstrates superior detection performance in this context. It is clearly shown in the figure that when SNR equals -10dB, the detection probability value of adaptive strategy is 0.4533, while the detection probability value of the traditional strategy is 0.7560, indicating a 66. 8% improvement in detection performance.

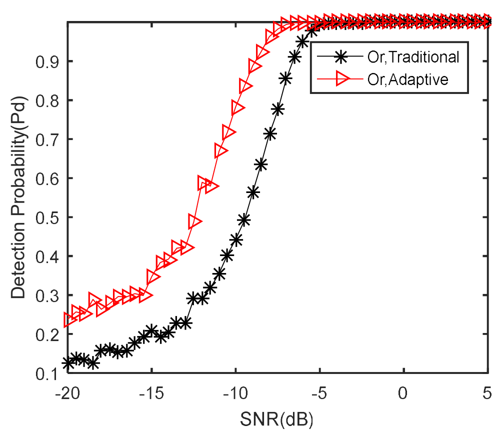


Figure 9: Pd vs. SNR under the "OR" criterion

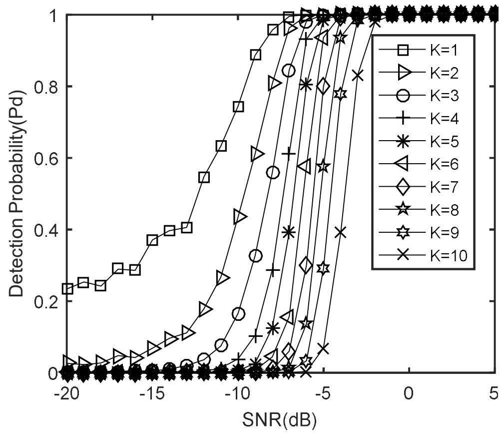


Figure 10: Pd vs. SNR for different CUs

Figure 10 illustrates how the performance of adaptive improved energy detection varies with the SNR for different numbers of cognitive users (CU). The number of secondary users ranges from 1 to 10, and both the "AND" and "OR" criteria are considered. The selected SNR values range from -20 dB to 5 dB. The analysis indicates that an increase in SNR correlates with an enhanced probability of detection. Furthermore, the "OR" criterion has the best detection performance, comparatively, the "AND" criterion has the worst detection performance.

## VI. Conclusions

This paper investigates cooperative spectrum sensing and presents a new adaptive double-threshold energy detection method aimed at enhancing the precision of spectrum resource management and utilization. Building upon existing energy detectors, we have made significant improvements, not only optimizing the detection mechanism but also ingeniously incorporating new understandings of signal characteristics. Specifically, we recognize that in wireless communication environments, signals tend to remain relatively stable over extremely short periods, meaning their statistical properties do not undergo significant changes within these timeframes. Based on this observation, we have devised a strategy that intimately links the current spectrum sensing results with those from immediately preceding and following moments. By comprehensively analyzing these time-series data, we have enhanced the accuracy and reliability of detection outcomes. Within the framework of cooperative spectrum sensing, we have selected the hard fusion decision rule as the processing strategy for the fusion center due to its simplicity and efficiency, enabling rapid global judgments based on individual node detections.

To evaluate the effectiveness of the proposed adaptive double-threshold energy detection method, comprehensive simulation experiments were performed utilizing MATLAB. The experimental results reveal that under optimal detection power exponent P (which does not equate to the conventionally assumed value of 2), a specific relationship pattern emerges between detection probability and SNR. Furthermore, we examined the operational efficiency of this method under varying false alarm probabilities and numbers of cognitive nodes. The experimental data clearly demonstrate that compared to traditional single-threshold or double-threshold detection algorithms, our proposed method exhibits a higher detection probability in low SNR environments and the system's detection performance has exceeded 50% improvement in both cases. This implies that even under poor signal quality conditions, we can more accurately identify the usage state of the spectrum, thereby effectively avoiding waste and conflicts in spectrum resource allocation.

In conclusion, the adaptive double-threshold energy detection technique presented in this paper not only enriches the theoretical framework of cooperative spectrum sensing but also provides robust technical support for spectrum management in practical applications. By enhancing detection probability and reducing misjudgment rates, this method is poised to play a pivotal role in future wireless communication networks, facilitating more efficient and rational utilization of spectrum resources.

## Funding

This research is supported by the Nature Science Foundation of Anhui Province Education Department under grant No. 2023AH051710 and Quality Engineering Projects No.2024jyxm0522, as well as by the Nature Science Foundation of Anhui SanLian University, which provided grants No. zjqr24003 and No. zjqr23004.

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