# Performance Evaluation of Energy Detection, Matched Filtering and KNN Under Different Noise Models

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**Abstract.** Due to the broadcast nature of radio transmission, both authorized and unauthorized users can access the network, which leads to the increasingly prominent security problems of wireless network. At the same time, it is more difficult to detect and identify users in wireless network environment due to the influence of noise. In this paper, the performance of energy detection (ED), matched filtering (MF) and K-nearest neighbor algorithm (KNN) are analyzed under different noise and uncertain noise separately. The Gaussian noise, α-stable distribution noise and Laplace distribution noise models are simulated respectively under the different uncertainty of noise when the false alarm probability is 0.01. The results show that the performance of the detectors is significantly affected by different noise models. In any case, the detection probability of KNN algorithm is the highest; the performance of MF is much better than ED under different noise models; KNN is not sensitive to noise uncertainty; MF has better performance on noise uncertainty which makes ED performance decline fleetly.

**Keywords:** Spectrum security · Radio monitoring · Noise uncertainty

## 1 Introduction

The amount of Internet of Things (IoT) devices based on wireless cellular network architecture has been increasing explosively with the advent of the 5G era, and the security of IoT has attracted much attention. Iot devices often suffer from various attacks, such as Denial of Service Attack (DoS), the User to Root Attack (U2R), Remote to Local Attack (R2L), and Probing Attack which may disrupt device workflow, impair product quality, and even lead to serious privacy issues and economic losses [1, 2]. In addition, the rapidly increasing IoT devices will not only bring convenience to daily life, but also bring greater consumption of mobile bandwidth, putting forward a higher requirement for radio spectrum safety and making radio monitoring particularly important. Identify the unauthorized radio users effectively is the basis of radio spectrum management [3].

Generally, the common methods for signal detection are cyclostationary feature detection [4], matched filter detection [5, 6], energy detection [7–9] and its improved


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algorithms [10–12]. ED and MF detection are the two most commonly used detection methods in radio monitoring [13], which have a good performance under Gaussian noise. However, there are many electromagnetic interferences in complex environment, resulting in many monitoring data accompanied by non-Gaussian noise. For example, the non-Gaussian noise that has a long tailed is described by α-stable distribution model [14, 15]; the impulse noise that generated by the electromechanical switches in the indoor environment, the lightning in the air and the wires in the outdoor environment [16], etc. A signal detection method based on matched filter under α-stable distribution noise is proposed in [17], which improves the detection performance of traditional matched filter in non-Gaussian noise environment; the method in [18] uses hyperbolic tangent function to suppress impulse noise, which obtains an improved robustness of detection under non-Gaussian noise. More unfortunately, the time-varying intensity of these non-Gaussian noises makes the noise change in a certain range, which seriously interferes with the signal detection process. And when the signal-to-noise ratio (SNR) of the signal detected is smaller than the threshold, the detector is no longer robust [19]. Different from the traditional methods, KNN algorithm based on ML learns from training samples, compares the new-coming signal sample with the training set, then labels the new-coming signal sample to reflect the specific attribute information, such as amplitude, phase, energy, frequency.

In this paper, the models of ED, MF and KNN under different noises are established and simulated to analyze the influence of different noises and noise with uncertain variance on the performance of the detectors (model). The remainder of this paper is organized as follows. Section 2 gives the signal model and detectors, Sect. 3 presents the simulation and analysis and Sect. 4 summarizes the whole paper.

## 2 Signal Model and Detectors

In this section, signal model and three detectors: ED, MF and the detector based on KNN algorithm are introduced respectively.

### 2.1 Signal Model

Signal existence detection mainly focuses on whether the signal exists in the channel. A binary hypothesis can be used to represent the detection problem of the signal:

$$\begin{aligned} H_0 &: x[n] = w[n] \\ H_1 &: x[n] = s[n] + w[n] \end{aligned}. \tag{1}$$

Here n = 1, 2, 3,…, N is the sampling time; $H_0$ refers to the absence of signal; H1 refers to the occurrence of signal; w[n] is the noise sequence; s[n] is the radio signal sequence; x[n] refers to the signal received by the radio monitoring station.

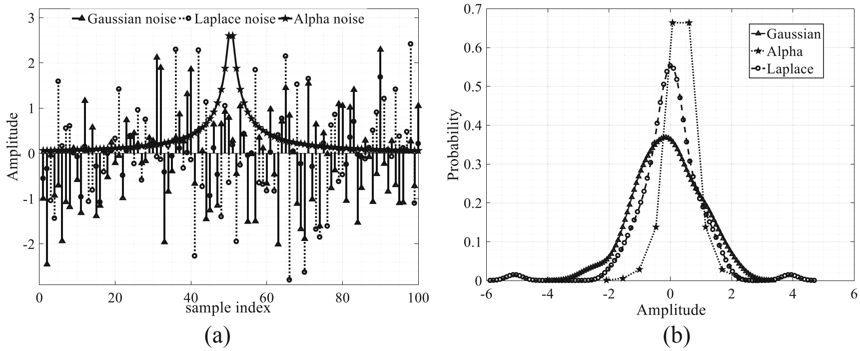



**Fig. 1.** Different noises wave with length of 100 (a) and their PDF (b). For the Gaussian noise, it has the parameters of $\mu = 0$, $\sigma^2 = 1$; the α-stable noise has the $\alpha = 0.5$, $\beta = 0$, $\gamma = 0.223$, $\mu = 0$, which has an obvious peak; Laplace noise with $\mu = 0$, $\sigma^2 = 1$, which has a heavy tail.

For convenience, we assume that $\{s[n]\}$, $\{w[n]\}$ are both independent and identically distributed, and they are independent of each other [20, 21]. In this paper, w[n] is studied by taking Gaussian noise [22], α-stable distribution noise [23] and Laplace noise [22] respectively. As shown in Fig. 1, the time-domain waveforms (a) and probability distribution curves (b) of the three noise models are given.

### 2.2 Detectors

**ED Detector.** ED is the best detection scheme when the radio signal information is unknown, which is widely used in the field of radio monitoring [13]:

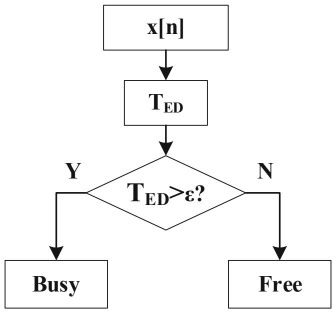



**Fig. 2.** Energy detection.

Figure 2 shows the processing of classical energy detection. After receiving x[n], the energy statistic $T_{ED}$ is calculated and compared with the threshold ε. When the energy statistic is bigger than ε, the channel is busy; otherwise, the channel is free. $T_{ED}$ is calculated by the Eq. (2):

$$T_{ED} = \frac{1}{N}\sum_{i=1}^{N}|x[i]|^2, \tag{2}$$

where the N is the length of signal sequence x[n].

**MF Detector.** MF is the best way when the radio signal is known [24, 25]:

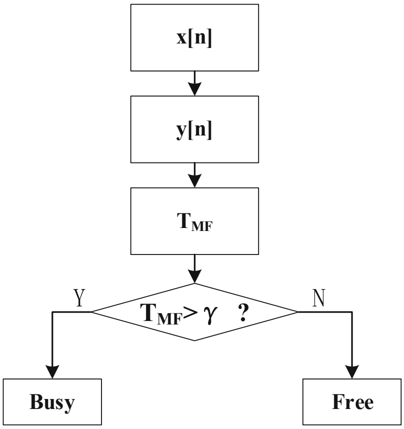



**Fig. 3.** Matched filter detection.

Figure 3 illustrates the process of matched filter detection. Assuming that the signal received by the matched filter is x[n]; the output of the matched filter is denoted as y[n], and the energy statistics is compared with the threshold $\gamma$ to determine the state of the channel. $T_{MF}$ is calculated by the following equation [25]:

$$T_{MF} = \frac{1}{N}\sum_{i=1}^{N}|C_m y[n]s[n]|, \tag{3}$$

where the Cm is the channel state information (CSI); s[n] is the radio signal sequence.

**KNN Detector.** KNN algorithm based on machine learning is a supervised learning algorithm [26], which needs to build training set and label.

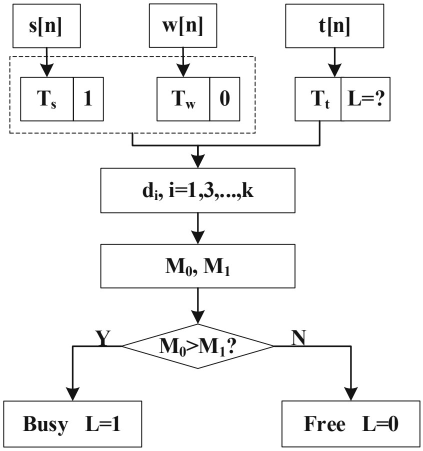



**Fig. 4.** Detection based on KNN algorithm.

Figure 4 depicts the process of method based KNN algorithm. The energy statistics are calculated form radio signal s[n] and labeled as 1; for noise w[n], the energy statistics are labeled as 0. In this way, we build a training set that includes data and tags showed as dotted box in Fig. 4, 75% of them are used as training data, 25% are used as testing data to test the performance of KNN. In addition, t[n] is the sample signal to be tested. Energy statistics are given by Eq. (4):

$$T_s = \frac{1}{N}\sum_{i=1}^{N}|s[i]|^2,\ T_w = \frac{1}{N}\sum_{i=1}^{N}|w[i]|^2,\ T_t = \frac{1}{N}\sum_{i=1}^{N}|t[i]|^2 \tag{4}$$

Euclidean distance is widely used as the measure distance of KNN algorithm. The Euclidean distance between any two samples X, Y is given by Eq. (5):

$$disy(X, Y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{5}$$

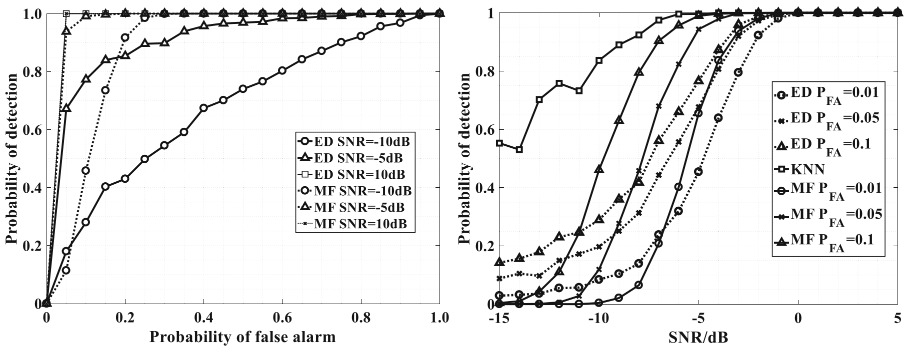
Distance between the energy statistics of t[n] and each sample in the training set is calculated, then K samples that is closest to the $T_t$ is selected to calculate the number $M_0$ and $M_1$ of $T_w$ and $T_S$. Finally, t[n] will be labeled with 0 when $M_0 > M_1$, otherwise with 1.

## 3 Simulation and Analysis

In order to analyze the performance of different detectors, we assume that the channel state information (CSI) is fixed, $C_m = 1$. The signal sequence is BPSK modulated signal, and the noise sequence is established according to the SNR.

### 3.1 Performance of Detectors Under Ideal Conditions

ED and MF have the best performance under Gaussian noise. The following experiments are performed at different false alarm probabilities:




(a) (b)

**Fig. 5.** Performance of detectors under Gaussian noise. (a) depicts the ROC curve of ED and MF; (b) describes the performance of detectors under different SNR. The detection probability of KNN is the highest; with the increase of false alarm probability, the detection probability of ED and MF is also increasing; under the same false alarm probability, the detection probability of MF is much higher than ED.

Figure 5 (a) indicates that probability of false alarm is helpful to improve the probability of detection, the detection probability of ED or MF is increased with the increasing of false alarm probability. On the other hand, under a certain false alarm probability, the higher the SNR is, the higher the detection probability will be.

Figure 5 (b) shows that under the simulated signal-noise environment, when $P_{FA}$ is equal to 0.01, the detection probability of MF reaches 1 near SNR $= -2.7$ db, and ED is 1 near SNR $= -1.5$ dB; the detection probability of MF reaches 1 near SNR $= -5$ dB, ED is 1 near SNR $= -1$ dB when $P_{FA} = 0.1$. In addition, the detection principle of KNN algorithm is very different from ED and MF, the probability of detection of KNN depends on the quality of the sample to be tested and the actual detection. KNN detector has excellent performance when the SNR $= -15$ dB, and the detection probability reaches 0.56, while the detection probability of ED and MF detector is smaller than 0.2; in any cases of $P_{FA}$, detection probability of KNN is the fastest detector to reach 1, which shows the great potential of KNN in radio monitoring.

### 3.2 Performance of Detectors Under Non-Gaussian Noise

Compared with the ideal Gaussian channel shown in Fig. 5, the performance of detectors changes greatly under non-Gaussian noise like α-stable distribution noise and Laplace distribution noise. The parameter configuration of the simulation experiment is shown in Table 1.

**Table 1.** Parameter configuration

| Items | Parameter/statement | Value | Items | Parameter/statement | Value |
|---|---|---|---|---|---|
| s[n] | BPSK | – | Gaussian Noise | $\mu$ (mean value) | 0 |
| K | Parameter of KNN algorithm | 3 | | $\sigma^2$(Variance) | 1 |
| $P_{FA}$ | Target false alarm probability | 0.01 | $\alpha$-stable Noise | $\alpha$ (Characteristic index) | 1 |
| Laplace noise | $\mu$ (mean value) | 0 | | $\beta$ (Symmetrical coefficient) | 0 |
| | $\sigma^2$( (Variance) | 1 | | $\gamma$ (Dispersion coefficient) | 0.223 |
| | $\lambda$ (scale parameter) | 0.7 | | $\mu$(Positional arguments) | 0 |
| $\rho$ | Noise uncertainty | [0, 3] | SNR | Signal to noise ratio | [−15, 15] |

In Table 1, the radio signal sequence s[n] is the BPSK modulated signal with length N = 100, which has a power 1; the noise power is calculated according to the SNR, and the noise sequence w[n] is obtained by multiplying the Gaussian noise with mean of 0 and variance of 1; K is the only parameter of KNN algorithm, and is the number of nearest neighbors; $P_{FA}$ is the target false alarm probability set in the following simulation experiment; there are three main parameters of Laplace noise: $\mu$ is the position parameter of Laplace noise, $\lambda$ is related to the variance of noise ($\sigma^2 = 2\lambda^2$); Generally, the larger $\lambda$ is, the longer the tail is when the position parameter $\mu$ is fixed; The $\alpha$-stable noise has a serious towing and the parameter $\alpha \in (0,2]$ determines the towing; The smaller $\alpha$ is, the more serious towing is. The symmetric parameter $\beta$ determines the inclination of the distribution. The larger the dispersion coefficient $\gamma$, the more dispersed the sample is relative to the mean value.

Taking the Gaussian noise detection probability curve as the baseline, the performance of both ED and MF decrease under the Laplace noise; under the $\alpha$-stable noise, the detection performance of MF improves rapidly, while the detection probability of ED decreases sharply. In addition, the detection probability of MF is higher than ED, which shows that MF has higher flexibility than ED in dealing with different noises. KNN has the highest detection probability under different noises. When the noises are non-Gaussian noises, the detection probability is maintained at 1 (Fig. 6).

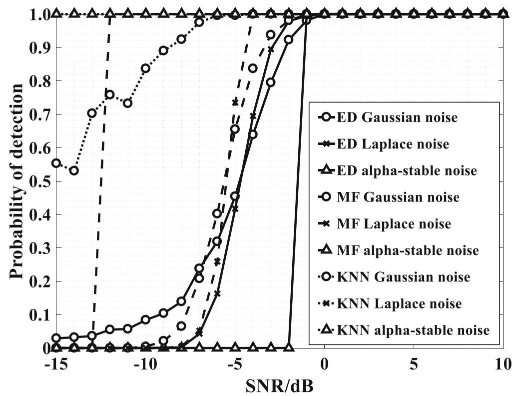



**Fig. 6.** Performance of detectors under different noise

Observingly, the detection probability curves of ED and MF under α-stable noise have a jump from 0 to 1 without any transition. Trying to adjust the parameters of a-distribution many times, but nothing is changed. Consider that it's related to noise characteristics, three kinds of noise waveforms are given in Fig. 1(a), which shows that α-stable noise only has a single pulse with a small amplitude in a limited range, while in other ranges its amplitude is generally close to 0.

### 3.3 Performance of Detectors with Uncertain Noise Variance

In practice, the noise is uneven and time-varying, which causes the variance to fluctuate in a certain range [20]. Analysis of the influence of noise uncertainty on the performance of three detectors under different noise.

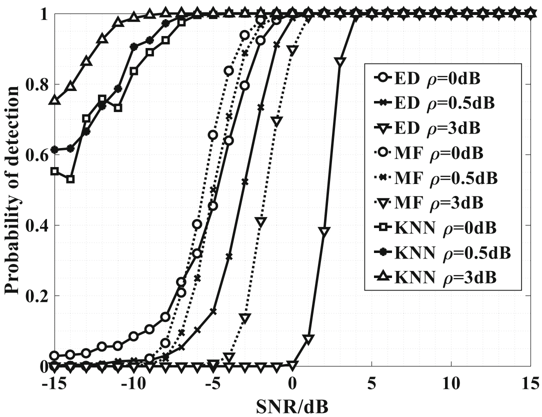



**Fig. 7.** Detection probability of three detectors under noise uncertainty in ideal Gaussian channel. The dotted line in the figure represents the detection probability curve of ED and the solid line represents the detection probability curve of MF.

Figure 7 points out that KNN has a good performance against noise uncertainty, and the increase of noise uncertainty does not reduce the detection probability of KNN. Even in an ideal Gaussian channel, the detection performance of ED and MF will be degraded due to the small uncertainty of Gaussian noise variance. With the uncertainty = 0 dB as the baseline, when the uncertainty of Gaussian noise was 0.1 dB, the ED detection probability curve moved down significantly and reached 1 at SNR = 0 dB, while the trend of MF detection probability curve was not as obvious as that of ED, and the detection probability reached 1 at SNR = −1.5 dB When the uncertainty of Gaussian noise is 3 dB, the ED detection probability curve drops significantly, the detection probability reaches 1 at SNR = 4 dB, and the MF detection probability reaches 1 at SNR = 0.

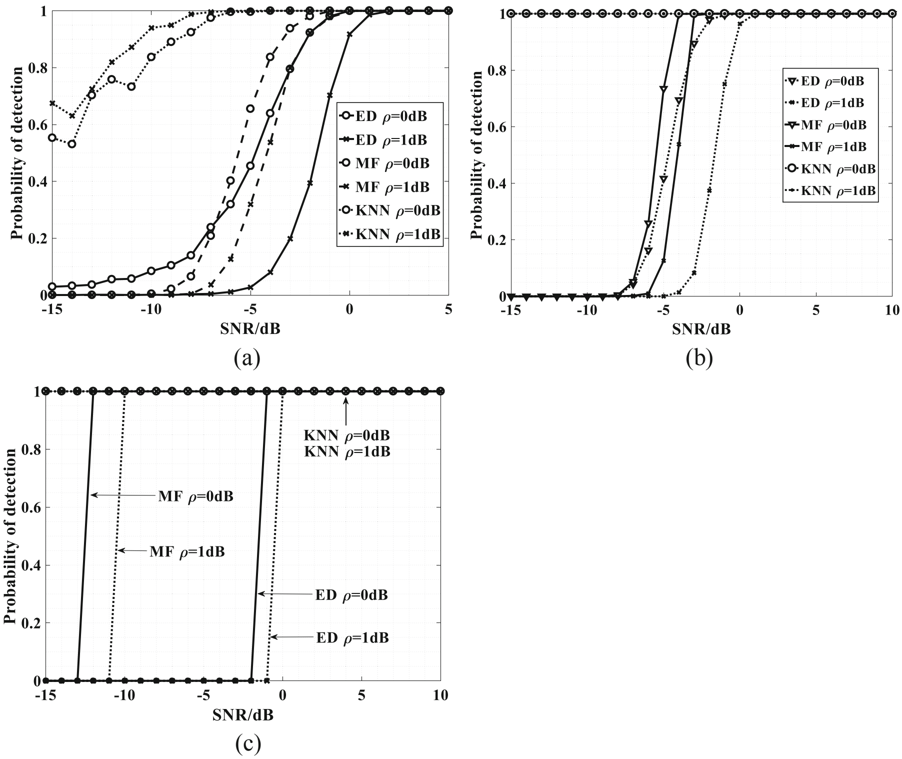



**Fig. 8.** Detection performance of three kinds of noise with uncertainty of ρ. (a) shows the detection probability of ED, MF and KNN when under Gaussian noise with uncertainty; (b) shows the detection probability of detector under Laplace noise with uncertainty; (c) shows the detection probability of detector under uncertain α-stable noise.

The simulation results in Fig. 8 show that whether Gaussian noise or non-Gaussian noise, once there is a small uncertainty in the noise variance, it will cause a great change in detection performance. As a result, the detection performance of ED and MF decreases; MF has a stronger ability to resist the uncertainty of noise than ED; KNN has a detection probability of 1 under non-Gaussian noise.

## 4 Conclusions

In this paper, the detection performance of ED, MF and KNN under different noise models are analyzed and simulated. The simulation results show that: 1) KNN is not sensitive to noise uncertainty, and the detection probability stays at 1 when dealing with non-Gaussian noise; 2) the detection probability of MF and ED under Gaussian noise model is higher than that under non Gaussian noise model; 3) under Gaussian or non-Gaussian noise model, MF has a higher detection probability than ED, MF holds a better performance to resist all kinds of noise; 4) considering the uncertainty of noise, the detection performance of MF and ED declines no matter what noise model; 5) under the same noise uncertainty, MF has a better detection probability than ED, MF holds a better performance to resist the noise with uncertainty of variance.

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