Statistical Covariance Based Signal Detection for Ambient Backscatter Communication Systems

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***Abstract*—Ambient backscatter, a new communication technology, can permit battery-free devices to communicate with other devices through reflecting the ambient radio frequency signals. One challenge for ambient backscatter communication system is to recover the backscattered information bits hidden in the received signals. Existing solutions are mainly based on energy detector and thus provide poor performance at low signal noise ratio (SNR). To solve this problem, a detection algorithm based on statistical covariances is suggested in this paper. Specifically, we calculate the distributions of two covariance-based statistics, design the detection rule, and then derive the closed-form expressions for detection probability and bit error rate (BER). It is found that our proposed algorithm outperforms the energy detector at low SNR regions. Finally, the simulation results are provided to corroborate our theoretical studies.**

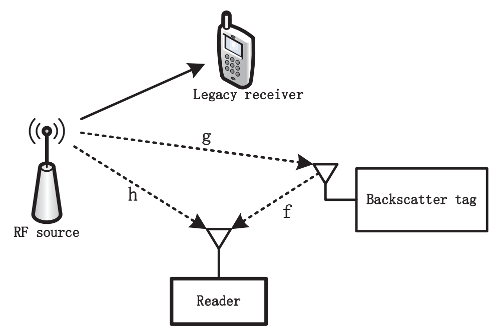

Fig. 1. The system model consisting of one reader and one tag

I. INTRODUCTION

Radio frequency identification (RFID), one key technology for Internet of Things (IoTs), attracts increasing interest from both academic world and industry circles [1]. One typical RFID system consists of a reader and a tag [2]. The reader first generates an electromagnetic wave, and the tag receives and backscatters the wave with modulated information bits to the reader. Clearly, the communication pattern for RFID system is backscattering instead of radiating the signals.

The radio backscatter communication could be traced back to World War II [2], and the first paper about backscatter communication was presented by Harry Stockman in 1948 [3]. From then on, the rapid progress in integrated circuits and the dropping cost of tags boost the fast development of RFID technology. In academia, extensive studies about backscatter communication have focused on channel fading and modelling [4], coding methods [5], link budgets [6] and multi-antenna techniques [7].

One well-known limitation for RFID applications is the communication range. The backscattered wave will suffer from a round-trip path loss, and therefore cannot be deployed in long-distance applications [4], [6], [7]. Meanwhile, it is energy-consuming for RFID systems, due to the energy compensation for the round-trip path loss at the reader.

To avoid this shortcoming, ambient backscatter, a new type of backscatter communication, was introduced by researchers at University of Washington in 2013 [8]. Different from traditional RFID, the tags in ambient backscatter communication systems are battery-free devices powered by ambient radio frequency (RF) signals, e.g., cellular signals, wireless fidelity (Wi-Fi) and television (TV) radio. The battery-free tags are able to transmit 1 and 0 bit by switching the antenna impedance to reflect the ambient signals or not. Next, the reader will utilize some algorithms to detect the two transmission statuses of the tag.

Existing detection algorithms for ambient backscatter system are mainly based on energy detector [8], [9], [10], which generally works well at high SNR, and produces high detection error at low SNR. Both the practical hardware implementation in [8] and the theoretical analysis in [10] further verified this for ambient backscatter systems.

In this paper, we propose a promising detection algorithm based on statistical covariances for ambient backscatter communication systems, and compute the probability of detection and bit error rate (BER). We also compare its detection performance with energy detector and show that the proposed algorithm outperforms the energy detector at low SNR.

The rest of the paper is organized as follows: Section II builds up the mathematical model for ambient backscatter systems and briefly illustrates energy-based detection algorithm. Section III introduces the new detector based on statistical covariances, and Section IV conducts performance analysis for the proposed detector. In Section V, the simulation results are presented to evaluate performances of those above two algorithms. Finally, the conclusions are provided in Section VI.

II. SYSTEM MODEL

As shown in Fig. 1, our ambient communication system consists of one RF source, one backscatter tag and one reader. The reader and the backscatter tag are equipped with single antenna. We denote the channel between the RF source and the reader as h, the channel between the RF source and the backscatter tag as g, and the channel between the backscatter tag and the reader as f. In this paper, we consider h, g and f are constants in one time slot. Assume the transmission bits transmitted from the tag to the reader in the nth time slot as $B(n)$.

The tag is able to receive the RF signals from the RF source, and at the same time communicate with the reader by backscattering the signal or not. When the backscatter tag reflects the signal to the reader, $B(n)$ is equal to 1; and when there is no reflection, $B(n)$ is set as 0. Thus, the signal received by the reader can be written as

$$y(n) = \begin{cases} hs(n) + w(n), & B(n) = 0, \\ hs(n) + \eta fgs(n) + w(n), & B(n) = 1, \end{cases} \tag{1}$$

where $w(n)$ is the zero-mean additive white Gaussian noise (AWGN) at the reader with the variance σ_w^2, and η is the amplitude attenuation when the signal transmits inside the tag. Note that the date rate of $B(n)$ should be much smaller than that of $s(n)$, i.e., $B(n)$ remains unchanged during the consecutive samples $s(n)$ in one time slot.

The main duty of the reader is to recover $B(n)$ from the received signal $y(n)$. To address this issue, the existing energy detector will first calculate the decision statistic as

$$Y = \begin{cases} \frac{1}{N_s}\sum_{n=1}^{N_s} |hs(n) + w(n)|^2, & B(n) = 0, \\ \frac{1}{N_s}\sum_{n=1}^{N_s} |(h + \eta fg)s(n) + w(n)|^2, & B(n) = 1. \end{cases} \tag{2}$$

Assume that $s(n)$ is a Gaussian random process with variance σ_s^2. According to central limit theorem, the statistic Y approximates as the Gaussian random variable:

$$B(n) = 0 : Y \sim N(\sigma_w^2 + h^2\sigma_s^2, \frac{2(\sigma_w^2 + h^2\sigma_s^2)^2}{N_s}), \tag{3}$$

$$B(n) = 1 :$$

$$Y \sim N(\sigma_w^2 + (h + \eta fg)^2\sigma_s^2, \frac{2(\sigma_w^2 + (h + \eta fg)^2\sigma_s^2)^2}{N_s}). \tag{4}$$

The detection probability P_d^e and the false alarm probability P_{fa}^e could be found as

$$P_d^e = P(T > \gamma^e|\mathcal{H}_1) = Q\left\{\frac{\gamma^e - \sigma_w^2 - (h + \eta fg)^2\sigma_s^2}{\sqrt{\frac{2(\sigma_w^2 + (h+\eta fg)^2\sigma_s^2)^2}{N_s}}}\right\}, \tag{5}$$

$$P_{fa}^e = P(T > \gamma^e|\mathcal{H}_0) = Q\left\{\frac{\gamma^e - \sigma_w^2 - h^2\sigma_s^2}{\sqrt{\frac{2(\sigma_w^2 + h^2\sigma_s^2)^2}{N_s}}}\right\}. \tag{6}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{+\infty} e^{-\frac{u^2}{2}}du$.

The threshold γ^e is set to meet the false alarm probability P_{fa}^e request as

$$\gamma^e = \sqrt{\frac{2(\sigma_w^2 + h^2\sigma_s^2)^2}{N_s}}Q^{-1}(P_{fa}^e) + \sigma_w^2 + h^2\sigma_s^2. \tag{7}$$

Assume $B(n) = 1$ and $B(n) = 0$ are equally probable, the BER could be expressed as

$$P_e^e = \frac{1}{2}P_{fa}^e + \frac{1}{2}(1 - P_d^e). \tag{8}$$

Since energy detector performs poorly at low SNR [11], we introduce a new promising algorithm based on statistical property to overcome this shortcoming in the next section.

III. STATISTICAL COVARIANCE BASED DETECTION ALGORITHM

In this section, we first exploit the statistical covariances property of the received signal $y(n)$, and next obtain a new way to recover the reflected information $B(n)$, and finally testify its feasibility.

A. Processes of the detection algorithm

We could perform the algorithm by three steps. The first step is to calculate the autocorrelations of the received signal as

$$\lambda(l) = \frac{1}{N_s}\sum_{m=0}^{N_s-1} y(m)y(m-l), l = 0, 1, ..., L-1, \tag{9}$$

where N_s is the number of available samples, and L is the number of consecutive samples.

Next step is to construct the approximated matrix $\hat{\mathbf{R}}_\mathbf{y}$ of the statistical covariances matrix $\mathbf{R}_\mathbf{y}$ as

$$\hat{\mathbf{R}}_\mathbf{y} = \begin{pmatrix} \lambda(0) & \lambda(1) & \ldots & \lambda(L-1) \\ \lambda(1) & \lambda(0) & \ldots & \lambda(L-2) \\ \vdots & \vdots & \ddots & \vdots \\ \lambda(L-1) & \lambda(L-2) & \ldots & \lambda(0) \end{pmatrix}. \tag{10}$$

The third step is to derive the following two statistics as

$$C_1(N_s) = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L} |r_{nm}|, B(n) = 1, \tag{11}$$

$$C_0(N_s) = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L} |r'_{nm}|, B(n) = 0, \tag{12}$$

where r_{nm} is the element at the nth row and the mth column in the covariances matrix $\hat{\mathbf{R}}_\mathbf{y}$ when $B(n) = 1$, and r'_{nm} refers to the element with the same pattern in $\hat{\mathbf{R}}'_\mathbf{y}$ when $B(n) = 0$.

We assume

$$C(N_s) = \begin{cases} C_0(N_s), & B(n) = 0, \\ C_1(N_s), & B(n) = 1. \end{cases} \tag{13}$$

Since the ratio $\frac{C(N_s)}{C_0(N_s)}$ corresponds to different results when $B(n)$ is different, we could employ the ratio $\frac{C(N_s)}{C_0(N_s)}$ to detect the presence of the reflected signal. The next section will prove its feasibility for ambient backscatter systems.

B. The feasibility of the proposed algorithm

For convenience of expression, we rewrite the sampled signals received by the reader as $y(n) = r(n) + w(n)$, where $r(n)$ is defined as

$$r(n) = \begin{cases} hs(n), & B(n) = 0, \\ (h + \eta f g)s(n), & B(n) = 1. \end{cases} \tag{14}$$

When the number of the available signal samples is large enough, Zeng and Liang have concluded the expectation of above statistics as [12]

$$\lim_{N_s \to \infty} E(C(N_s)) = \frac{2\sigma_r^2}{L} \sum_{l=1}^{L-1} (L-l)|\alpha_l| + \sigma_r^2 + \sigma_w^2, \tag{15}$$

where σ_r^2 denotes the power of signal $r(n)$, and α_l is the normalized correlation among the N_s signal samples, which is expressed as

$$\alpha_l = \frac{E[r(n)r(n-l)]}{\sigma_r^2}. \tag{16}$$

The expression (15) could be simplified as

$$\lim_{N_s \to \infty} E(C(N_s)) = \frac{2}{N_s L} \sum_{l=1}^{L-1} (L-l) |\sum_{n=1}^{N_s} r(n)r(n-l)| + \sigma_r^2 + \sigma_w^2. \tag{17}$$

Compared with the scenario (Scenario 0) where the backscatter tag does not reflect the signal, in the counterpart scenario (Scenario 1), the reader could access one more path signal from the tag. Thus, we have

$$\sigma_{r1}^2 > \sigma_{r0}^2, \tag{18}$$

where σ_{r1}^2, σ_{r0}^2 represent the power of received signal $r(n)$ for $B(n) = 1$ and $B(n) = 0$, respectively. And σ_w^2 remains equal in two different scenarios, so the problem is to prove whether the first term of the expression (17) in scenario 1 is greater than the one in scenario 0 or not. When $B(n) = 1$, we have

$$|\sum_{n=1}^{N_s} r(n)r(n-l)| = (h + \eta f g)^2 |\sum_{n=1}^{N_s} s(n)s(n-l)|. \tag{19}$$

When $B(n) = 0$, we have

$$|\sum_{n=1}^{N_s} r(n)r(n-l)| = h^2 |\sum_{n=1}^{N_s} s(n)s(n-l)|. \tag{20}$$

Since the signal sample $s(n)$ is definitely correlated for the following three reasons: (1) the oversampled signal, (2) the propagation channel, and (3) the originally correlated signal [12], so $|\sum_{n=1}^{N_s} s(n)s(n-l)|$ is not equal to zero. When the expression (19) divides the expression (20), we have the ration $(1 + \frac{\eta f g}{h})^2$. In this case, if $\frac{\eta f g}{h} > 0$ or $\frac{\eta f g}{h} < -2$, we have the value of $|\sum_{n=1}^{N_s} r(n)r(n-l)|$ in scenario 1 is bigger than the one in scenario 0. Then, we are able to conclude that

$$\frac{2}{N_s L} \sum_{l=1}^{L-1} (L-l) |\sum_{n=1}^{N_s} r_1(n)r_1(n-l)| > \frac{2}{N_s L} \sum_{l=1}^{L-1} (L-l) |\sum_{n=1}^{N_s} r_0(n)r_0(n-l)|. \tag{21}$$

From expressions (17), (18), and (21), when the available number of the signal samples is large enough and $\frac{\eta f g}{h} > 0$ or $\frac{\eta f g}{h} < -2$, we have $E(C_1(N_s)) > E(C_0(N_s))$. Since the authors in [12] conclude $E(C_1(N_s)) \approx C_1(N_s)$ and $E(C_0(N_s)) \approx C_0(N_s)$, we can write our detection algorithm as, if there is no reflected signal, $\frac{C(N_s)}{C_0(N_s)} \approx \frac{E(C_0(N_s))}{E(C_0(N_s))} = 1$; and if the signal is present, $\frac{C(N_s)}{C_0(N_s)} \approx \frac{E(C_1(N_s))}{E(C_0(N_s))} > 1$. Therefore, the ratio $\frac{C(N_s)}{C_0(N_s)}$ could be exploited to detect the presence of the reflected signal and the proposed algorithm fits ambient backscatter systems.

IV. Performance analysis

In this section, we first derive the distributions of the statistics $C_1(N_s)$ and $C_0(N_s)$, and then calculate the expressions of the detection probability and BER.

A. Statistics computation

The authors in [12] conclude that the distribution of the statistic $C(N_s)$ closes to the Gaussian distribution when the signal appears. The expectation of $C(N_s)$ is given in (17). The variance, another element to decide the Gaussian distribution, is derived by the following computations. Firstly, we could obtain the expectation of the $|\lambda(l)|^2$ as

$$E(|\lambda(l)|^2) = \frac{1}{\sqrt{2\pi\Delta_l}} \int_{-\infty}^{\infty} |u|^2 e^{-\frac{(u-\theta_l)^2}{2\Delta_l}} du, \tag{22}$$

where θ_l and Δ_l denote the expectation $E(\lambda(l))$ and the variance var$(\lambda(l))$ of $\lambda(l)$, respectively [12]. We employ the simplified raw absolute moments of Gaussian variable from [13] and then have

$$E(|\lambda(l)|^2) = \Delta_l 2 \frac{\Gamma(\frac{3}{2})}{\sqrt{\pi}} {}_1F_1(-1; \frac{1}{2}; -\frac{1}{2}(\frac{\theta_l^2}{\Delta_l})), \tag{23}$$

where $\Gamma(x) = \int_0^\infty e^{-t} t^{x-1} dt$ is a Gamma function, and ${}_1F_1$ is the confluent hypergeometric function [14], which is defined as

$${}_1F_1(a; b; z) = \sum_{n=0}^{\infty} \frac{a^{(n)} z^n}{b^{(n)} n!}, \tag{24}$$

where:

$$a^{(0)} = 1, \tag{25}$$

$$a^{(n)} = a(a+1)(a+2)...(a+n-1). \tag{26}$$

We can obtain $E(C_1(N_s))$ as

$$
\begin{aligned}
E(C_1(N_s)) &= E\left[\frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}|\right] \\
&= E[\lambda(0) + \frac{2}{L}\sum_{l=1}^{L-1}(L-l)|\lambda(l)|] \\
&= E(\lambda(0)) + \frac{2}{L}\sum_{l=1}^{L-1}(L-l)E(|\lambda(l)|). \quad (27)
\end{aligned}
$$

Similarly, $E(C_1(N_s)^2)$ can be expressed as

$$
\begin{aligned}
E(C_1(N_s)^2) &= E[\lambda(0)^2 + \frac{4}{L}\lambda(0)\sum_{l=1}^{L-1}(L-l)|\lambda(l)| \\
&\quad + \frac{4}{L^2}(\sum_{l=1}^{L-1}(L-l)|\lambda(l)|)^2] \\
&= E[\lambda(0)^2] + \frac{4}{L}E(\lambda(0))\sum_{l=1}^{L-1}(L-l)E(|\lambda(l)|) \\
&\quad + \frac{4}{L^2}\sum_{l_1=1}^{L-1}\sum_{l_2=1}^{L-1}(L-l_1)(L-l_2)E(|\lambda(l)|)^2 \\
&\quad + \frac{4}{L^2}\sum_{l=1}^{L-l}(L-l)^2E(|\lambda(l)|^2)\ (l_1 \neq l_2). \quad (28)
\end{aligned}
$$

Based on equations (27) and (28), we can obtain the variance of $C_1(N_s)$ as

$$
\begin{aligned}
&\text{var}(C_1(N_s)) = E(C_1(N_s)^2) - E(C_1(N_s))^2 \\
&= \frac{4}{L^2}\sum_{l=1}^{L-1}(L-l)^2(E(|\lambda(l)|^2) - E(|\lambda(l)|)^2) + \text{var}(\lambda(0)). \quad (29)
\end{aligned}
$$

Similarly, we could also have $E(C_0(N_s))$ and $\text{var}(C_0(N_s))$.

B. Detection probability, BER and associated threshold

By substituting (23) and computation results from [12], equations (27) and (29) could be rewritten as

$$
E(C_1(N_s)) = \sigma_r^2 + \sigma_w^2 + \frac{2\sigma_r^2}{L}\sum_{l=1}^{L-1}(L-l)|\alpha_l|, \quad (30)
$$

$$
\begin{aligned}
&\text{var}(C_1(N_s)) = \frac{2\sigma_w^2}{N_s}(2\sigma_r^2 + \sigma_w^2) \\
&+ \frac{4}{L^2}\sum_{l=1}^{L-1}(L-l)^2(\Delta_l 2\frac{\Gamma(\frac{3}{2})}{\sqrt{\pi}}{}_1F_1(-1;\frac{1}{2};-\frac{1}{2}(\frac{\theta_l^2}{\Delta_l})) \\
&- (\sqrt{\frac{2}{\pi N_s}}(\sigma_r^2 + \sigma_w^2)(2 - e^{-\frac{\tau_l^2}{2}}) + |\theta_l|(1 - 2Q(\tau_l)))^2), \quad (31)
\end{aligned}
$$

Similarly, we can have the expressions of the expectation and variance of $C_0(N_s)$, i.e., $E(C_0(N_s))$ and $\text{var}(C_0(N_s))$. Thus, the false alarm probability P_{fa}^c is obtained as

$$
\begin{aligned}
P_{fa}^c &= P(C(N_s) > \gamma^c C_0(N_s)|B(n) = 0) \\
&= P(C_0(N_s) < \frac{1}{\gamma^c}C(N_s)|B(n) = 0) \\
&\approx P(C_0(N_s) < \frac{1}{\gamma^c}E(C_0(N_s))|B(n) = 0) \\
&= P\left(\frac{C_0(N_s) - E(C_0(N_s))}{\sqrt{\text{var}(C_0(N_s))}} < \frac{(\frac{1}{\gamma^c} - 1)E(C_0(N_s))}{\sqrt{\text{var}(C_0(N_s))}}\right) \\
&\approx 1 - Q\left\{\frac{(\frac{1}{\gamma^c} - 1)E(C_0(N_s))}{\sqrt{\text{var}(C_0(N_s))}}\right\}. \quad (32)
\end{aligned}
$$

Therefore, for a given P_{fa}^c, we can obtain the threshold as

$$
\gamma^c = \frac{E(C_0(N_s))}{E(C_0(N_s)) + Q^{-1}(1 - P_{fa}^c)\sqrt{\text{var}(C_0(N_s))}}. \quad (33)
$$

Accordingly, the probability of detection P_d^c can be expressed as

$$
\begin{aligned}
P_d^c &= P(C(N_s) > \gamma^c C_0(N_s)|B(n) = 1) \\
&= P(C_0(N_s) < \frac{1}{\gamma^c}C(N_s)|B(n) = 1) \\
&\approx P(C_0(N_s) < \frac{1}{\gamma^c}E(C_1(N_s))|B(n) = 1) \\
&= P\left(\frac{C_0(N_s) - E(C_0(N_s))}{\sqrt{\text{var}(C_0(N_s))}}\right. \\
&\quad \left. < \frac{\frac{1}{\gamma^c}E(C_1(N_s)) - E(C_0(N_s))}{\sqrt{\text{var}(C_0(N_s))}}\right) \\
&\approx 1 - Q\left\{\frac{\frac{1}{\gamma^c}E(C_1(N_s)) - E(C_0(N_s))}{\sqrt{\text{var}(C_0(N_s))}}\right\}. \quad (34)
\end{aligned}
$$

Finally, in the case of equally possible $B(n) = 1$ and $B(n) = 0$, the expression of BER P_e^c can be found as

$$
P_e^c = \frac{1}{2}P_{fa}^c + \frac{1}{2}(1 - P_d^c). \quad (35)
$$

V. Simulation Results

In this section, we corroborate our proposed studies by simulation results. We assume the number of available samples N_s as 5000, and the smoothing factor L as 5. The channel parameters are set as $h = 0.5$, $g = 0.5$, and $f = 0.5$, and they meet the condition $\frac{\eta f g}{h} > 0$. The amplitude attenuation η inside the tag is 0.1. The noise variance is defined as $\sigma_w^2 = 1$. And the autocorrelation values of the RF singles is set as $\lambda(1) = 0.1$, $\lambda(2) = 0.2$, $\lambda(3) = 0.3$ and $\lambda(4) = 0.4$. Assume $s(n)$ is zero-mean Gaussian distribution with variance σ_s^2, and $\sigma_s^2 = \mathit{SNR} \times \sigma_w^2$.

Fig. 2 depicts the curves of BER versus the increasing SNR from -4dB to 3dB. It can be seen that both BERs of two detection algorithms decrease when SNR increases. Besides, it is found that the proposed algorithm outperforms the energy detector at low SNR regions.

Fig. 3 gives the curves of probability of detection versus SNR for two different detections. It can be readily checked

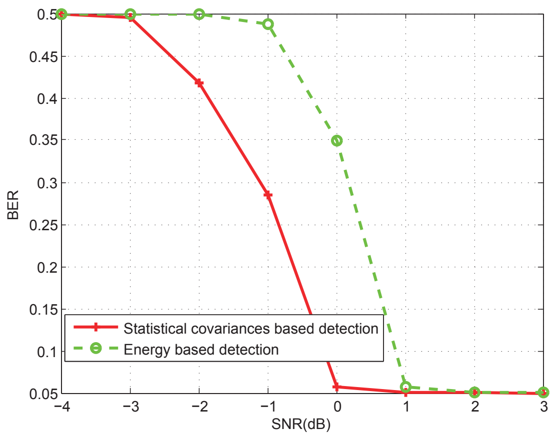

Fig. 2. BER curves for two detection algorithms: $P_{fa} = 0.1$.

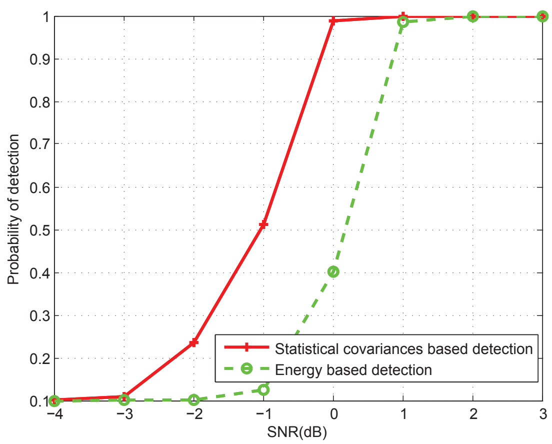

Fig. 3. Probability of detection curves for two detection algorithms when SNR increases: $P_{fa} = 0.1$.

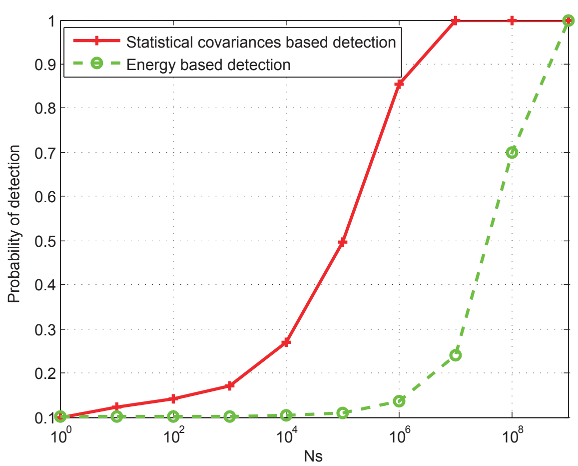

Fig. 4. Probability of detection curves for two detection algorithms when N_s increase: $P_{fa} = 0.1$, SNR=-2 dB.

that the probabilities of detection for two different detection algorithms at higher SNR are bigger than those at lower SNR. Also, the algorithm based on statistical covariances has a better performance than the energy detection at low SNR with the gain as large as 1.5 dB. When SNR is bigger than one threshold, the probabilities of detection for the proposed algorithm and the energy based detection algorithm are almost the same.

In Fig. 4, the curves of detection probability for two algorithms versus the number of the available samples N_s are shown. It is illustrated that those two algorithms tend to have the same performance when N_s is big enough. However, the proposed algorithm outperforms the energy detection when N_s is at low.

VI. Conclusion

In this paper, a new detection algorithm based on statistical covariances for ambient backscatter communication system was proposed. The corresponding performance of the new detector, e.g., BER and detection probability, was analyzed. It was shown the suggested algorithm could outperform the energy detector in terms of the BER and the detection probability at low SNR with the gain as large as 1.5 dB.

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