Symbiotic Radio Systems: Detection and Performance Analysis

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Abstract: Symbiotic radio (SR) is an emerging green technology for the Internet of Things (IoT). One key challenge of the SR systems is to design efficient and low-complexity detectors, which is the focus of this paper. We first drive the mathematical expression of the optimal maximum-likelihood (ML) detector, and then propose a suboptimal iterative detector with low complexity. Finally, we show through numerical results that our proposed detector can obtain near-optimal bit error rate (BER) performance at a low computational cost.

Keywords: bit error rate; data detection; Internet of Things; symbiotic radio system; wireless communication

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1 Introduction

The Internet of Things (IoT) enables large-scale connection of IoT devices and is regarded as one of the major applications for the fifth-generation (5G) communication networks. However, due to the huge number of IoT devices, traditional IoT communication technologies inevitably face huge energy consumption problem and a shortage of spectrum resources. The two factors have become bottlenecks in the development and implementation of IoT[1–2].

Ambient backscatter communication (AmBC) is a promising technology to address the above bottlenecks. It enables passive backscatter devices (like passive tags) to harvest energy from ambient signals such as WiFi, broadcast TV, or cellular signals, and to modulate information by dynamically adjusting the impedance inside the circuits without using any specific RF components[3–4]. Unfortunately, as a result of the spectrum-sharing nature and the double attenuation of the backscatter link, the prime signal (from RF sources) is usually stronger than the backscattered signal (transmitted by the backscatter device) and is usually taken as interference to the reader, leading to a severe error floor problem[5–7].

Recently, symbiotic radio (SR) system has been proposed to tackle prime signal interference[2, 8–9]. The simplest SR system consists of a prime transmitter (PT), a tag, and a reader, in which the PT not only serves as an energy source to support backscatter communication but also transmits its own information. Thus, the reader needs to recover the information from the PT and the tag. Benefitting from the cooperative communication property, the SR system converts the prime signal interference to useful information, yielding a higher achievable rate than the traditional AmBC system[10–11].

A key challenge of the SR system is to design effective and efficient detectors. The main difficulties are as follows. First, the prime signal and the backscattered signal are mutually dependent (formulated in Section 2), making it difficult to recover the information carried by received signals. Second, the computational complexity of the optimal detectors is relatively high, and grows rapidly as the modulation order of the PT and the tag increases, causing non-negligible decoding time consumption that may exceed the strict response time constraint of some specific IoT protocols like the industrial RFID Gen2 protocol[12].

In order to realize effective and efficient signal detection for the SR system, it is worth studying detectors that provide desirable performance but with low complexity. Related research is still in its infancy. In Ref. [13–14], the authors proposed low-complexity linear detectors and successive interference cancellation (SIC) based detectors to recover bits from the PT and the tag.

The effective and efficient detector design is a practical constraint for the SR system but is rarely studied at present, which motivates our current work. In this paper, we investigate the signal detection problem of the SR system. The contributions of our work are summarized as follows:

First, we formulize the system model of the SR system, and derive the optimal maximum-likelihood (ML) detector which is optimal when all the symbols are equiprobable.

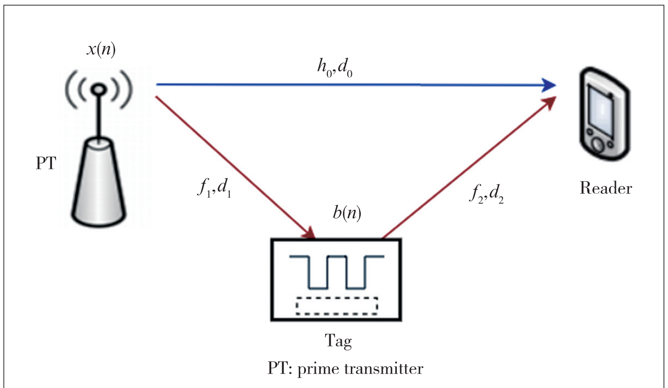
Then, considering that the prime signal is much stronger than the backscatter signal, we propose a suboptimal iterative detector with polynomial complexity. In each iteration, the suboptimal iterative detector detects the prime signal, and then detects the backscatter signal using the knowledge from the detected prime signal.

Finally, we numerically analyze the bit error rate (BER) performance of the proposed suboptimal detector. Simulation results demonstrate that the performance of the proposed detector becomes stable after about two rounds of iteration, and its performance is close to the optimal ML detector for typical application scenarios.

The rest of this paper is organized as follows. Section 2 introduces the system model under consideration. Section 3 derives the optimal ML detector and proposes a suboptimal iterative detector that can reduce the computational complexity while obtaining near-optimal detection performance. Section 4 numerically evaluates the BER performance of the proposed detector. Finally, Section 5 summarizes this paper.

2 System Model

Fig. 1 depicts a symbiotic radio system that consists of a PT, a passive tag, and a reader. In this system, the tag harvests RF energy from the PT, and then modulates its information by varying the antenna load impedance. Compared with the traditional ambient backscatter system, the PT is designed to provide power to the tag and to enable communications. Therefore, the reader receives superposed signals from the PT and the tag. Thus, it needs to recover the information from both of the two devices.



▲**Figure 1. Symbolic radio system model**

Let d_0 represent the distance between the PT and the reader, d_1 represent the distance between the PT and the tag, and d_2 represent the distance between the tag and the reader. In this paper, we consider the block fading channel model, which means the channel states are static during one time slot. Let h_0, f_1, and f_2 be the channel coefficients from the PT to the reader, the PT to the tag, and the tag to the reader, respectively. We assume h_0, f_1 and f_2 are mutually independent, each of which follows the Rician distribution as

$$q \sim CN\left(\sqrt{\frac{k_q}{k_q+1}\sigma^2}, \frac{\sigma_q^2}{k+1}\right), q \in \{h_0, f_1, f_2\}, \tag{1}$$

where k_q is the ratio of the energy in the specular path to the energy in the scattered path[15–16]. Let $k_q = 0$, and Rayleigh fading is obtained. Noting that the channel state can be estimated using pilot signals[17], we assume that perfect channel state information (CSI) is available.

Let $x(n) \in \mathcal{A}_x$, and $b(n) \in \mathcal{A}_b$ denote the transmitted signal of the PT and the tag at the n-th time slot, respectively, where $\mathcal{A}_x$ stands for the modulation alphabet set of the PT and $\mathcal{A}_b$ stands for the modulation alphabet set of the tag. The signal power of the PT is represented by P_x.

In this paper, we assume the data rate of the tag equals that of the reader. Therefore, the signal received by the reader in the n-th time slot is

$$y(n) = \frac{h_0}{\sqrt{d_0^{\alpha}}}x(n) + \eta\frac{f_1}{\sqrt{d_1^{\alpha}}}\frac{f_2}{\sqrt{d_2^{\alpha}}}x(n)b(n) + \omega(n), \tag{2}$$

where η is the attenuation inside the tag, and $\omega(n)$ is the complex additive white Gaussian noise (AWGN) with zero-mean and σ^2 variance.

Eq. (2) can be simplified as:

$$y(n) = \mu x(n) + \nu x(n)b(n) + \omega(n), \tag{3}$$

where

$$\mu = \frac{h_0}{\sqrt{d_0^{\alpha}}}, \tag{4}$$

$$\nu = \eta\frac{f_1}{\sqrt{d_1^{\alpha}}}\frac{f_2}{\sqrt{d_2^{\alpha}}}. \tag{5}$$

For convenience, we define the signal-to-noise ratio (SNR) of the prime link as $\gamma_P \triangleq \frac{P_x\mathbb{E}[|\mu|^2]}{\sigma^2}$, and the SNR of the backscatter link as $\gamma_B \triangleq \frac{P_xP_b\mathbb{E}[|\nu|^2]}{\sigma^2}$.

Strictly speaking, the arrival of $b(n)$ is delayed by time $\tau (\tau \geqslant 0)$ compared with $x(n)$. However, such delay can be ignored in most scenarios for the following reasons[3, 13, 18]. First, the tag is close to the reader with a distance usually less than 10 feet (3.048 m). Second, the signal transmission speed inside the tag circuit is so fast that the transmission delay is too short to impact the signal detection.

3 Data Detection for Symbiotic Radio Systems

In this section, we first introduce the optimal ML detector for the SR system utilizing the perfect CSI, and then propose a suboptimal iterative detector.

3.1 Optimal ML Detector

The ML detector is the most suitable when all the symbols are equiprobable. The ML detection rule is given by:

$$\left\{\hat{x}(n),\hat{b}(n)\right\} = \arg\max_{\substack{x(n)\in\mathcal{A}_x,\\ b(n)\in\mathcal{A}_b}} f\left(y(n)|x(n),b(n)\right), \tag{6}$$

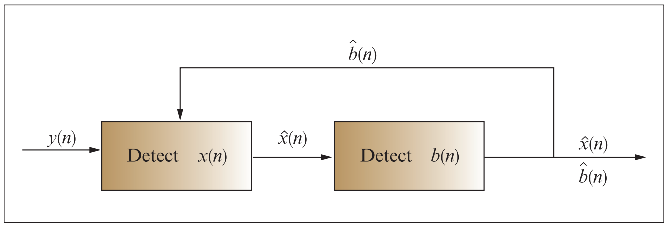
where $\hat{x}(n)$ and $\hat{b}(n)$ are detected bits of the PT and the tag, respectively. Eq. (6) can also be written as:

$$\left\{\hat{x}(n),\hat{b}(n)\right\} = \arg\min_{\substack{x(n)\in\mathcal{A}_x,\\ b(n)\in\mathcal{A}_b}} \left|y(n) - \mu x(n) - \nu x(n)b(n)\right|^2. \tag{7}$$

Note that the searching time of the optimal ML detector is $\left|\mathcal{A}_x\right| \cdot |\mathcal{A}_b|$, and it will increase rapidly when the PT and the tag use high-order modulation. We then propose a suboptimal iterative detector with relatively low complexity.

3.2 Suboptimal Iterative Detector

In the SR system, the prime signal $\mu x(n)$ is stronger than the backscatter signal $\nu x(n)b(n)$ due to the double attenuation of the backscatter link. Therefore, $x(n)$ can be recovered first with desirable performance by taking $\nu x(n)b(n)$ as noise. Then the detector subtracts $\mu\hat{x}(n)$ from the received signal $y(n)$ to construct new statistic to recover $\hat{b}(n)$. In this process, some recovered symbols may be erroneous. However, $\hat{b}(n)$ can be fed back to the detector to improve the detection performance. The same is true for $\hat{x}(n)$. After repeating this process several times, the detector will obtain desirable performance. Fig. 2 shows the block diagram of this procedure. Next, we introduce the detail process of the suboptimal iterative detector.



▲**Figure 2. Suboptimal iterative detector scheme**

1) Detect $x(n)$

Considering that the prime signal is stronger than the backscatter signal, we first use the ML detector to recover $x(n)$ while taking $\nu x(n)b(n)$ as noise. Under this circumstance, the detection rule is:

$$\hat{x}(n) = \arg\min_{x(n)\in\mathcal{A}_x} \left|y(n) - \mu x(n)\right|^2. \tag{8}$$

2) Detect $b(n)$

After obtaining $\hat{x}(n)$, the prime signal inference can be removed by subtracting $\mu\hat{x}(n)$ from the received signal $y(n)$. This can be written as

$$y_2(n) = y(n) - \mu\hat{x}(n). \tag{9}$$

Then with the use of the ML detector, $\hat{b}(n)$ is given by

$$\hat{b}(n) = \arg\min_{b(n)\in\mathcal{A}_b} \left|y_2(n) - \nu\hat{x}(n)b(n)\right|^2. \tag{10}$$

3) Iterative manner

The detection results of process (1) and process (2) may be erroneous. Fortunately, the existing work shows that the detection performance can be improved using the iterative detection manner[19]. Therefore, we can redetect $x(n)$ as Eq. (11), and then substitute redetected $\hat{x}(n)$ into Eq. (10) to update $\hat{b}(n)$. After a few iterations, the suboptimal detector can get desirable performance.

$$\hat{x}(n) = \arg\min_{x(n)\in\mathcal{A}_x} \left|y(n) - \mu x(n) - \nu x(n)\hat{b}(n)\right|^2. \tag{11}$$

We summarize the algorithm of the suboptimal detector in Algorithm 1. In each iteration, the detector needs to search $\left|\mathcal{A}_x\right|$ possible values to recover $x(n)$ and $\left|\mathcal{A}_b\right|$ possible values to recover $b(n)$. Moreover, this algorithm repeats K times, so the overall search time of the suboptimal iterative detector is $K(\left|\mathcal{A}_x\right| + \left|\mathcal{A}_b\right|)$. Considering K is a preset constant and usually a small value, the computational complexity of the suboptimal detector is $O(\left|\mathcal{A}_x\right| + \left|\mathcal{A}_b\right|)$.

Algorithm 1. Suboptimal Iterative Detection

Input: $\mathcal{A}_x, \mathcal{A}_b, y(n), \mu, \nu$
Output: $\hat{x}(n), \hat{b}(n)$
$\hat{x}(n) = \arg\min_{x(n)\in\mathcal{A}_x} \left|y(n) - \mu x(n)\right|^2$
While $K \neq 0$
    $y_2(n) = y(n) - \mu\hat{x}(n)$
    $\hat{b}(n) = \arg\min_{b(n)\in\mathcal{A}_b} \left|y_2(n) - \nu\hat{x}(n)b(n)\right|^2$
    $\hat{x}(n) = \arg\min_{x(n)\in\mathcal{A}_x} \left|y(n) - \mu x(n) - \nu x(n)\hat{b}(n)\right|^2$
    $K \leftarrow K - 1$
End While

4 Numerical Results

In this section, we analyze the detection performance of the proposed suboptimal iterative detector. We first compare the suboptimal detector with the optimal ML detector and the linear minimum mean-square-error (LMMSE) detector, and then investigate the performance of the suboptimal detector in different iterations. The expression of the LMMSE detector can be found in Ref. [20]. We summarize the computational complexity of the three detectors in Table 1.

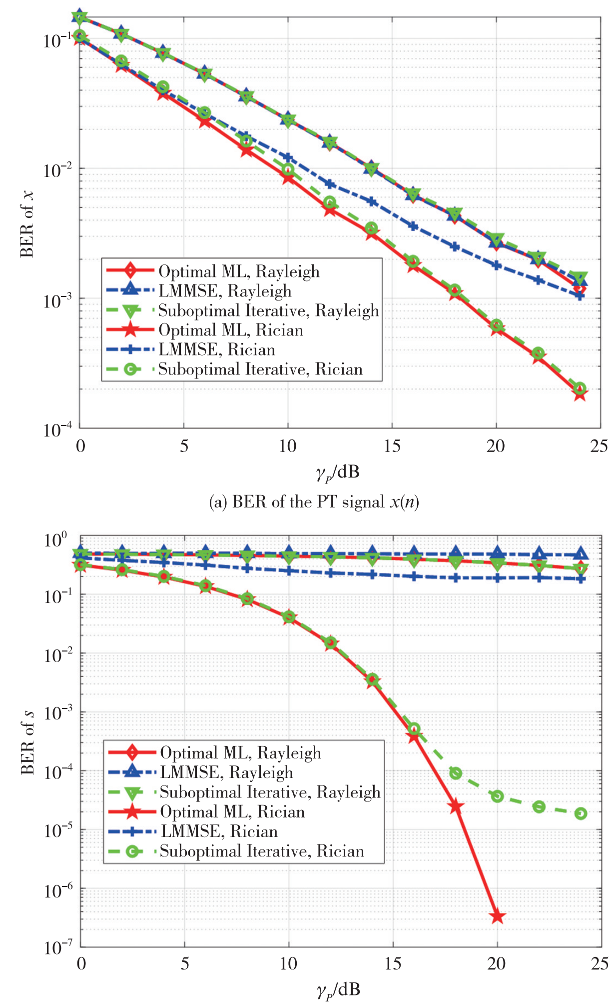
▼**Table 1. Computational complexity of different detectors**

Detector	Computational Complexity
Optimal ML	$O(\lvert\mathcal{A}_x\rvert \cdot \lvert\mathcal{A}_b\rvert)$
LMMSE	$O(\lvert\mathcal{A}_x\rvert \cdot \lvert\mathcal{A}_b\rvert)$
Suboptimal iterative	$O(\lvert\mathcal{A}_x\rvert + \lvert\mathcal{A}_b\rvert)$

LMMSE: linear minimum mean-square-error　　ML: maximum-likelihood

We consider that the PT uses the binary phase shift keying (BPSK) modulation and the tag uses on-off keying (OOK) modulation. Therefore, $\mathcal{A}_x = \left\{\sqrt{P_x}, -\sqrt{P_x}\right\}$, and $\mathcal{A}_b = \{0, 1\}$. Specifically, $b(n) = 1$ means that the tag backscatters signals, and $b(n) = 0$ means that the tag does not backscatter signals. We assume that the tag attenuation $\eta = 0.8$, path loss factor $\alpha = 2$, channel parameter $k_q = 20$, and the noise variance $\sigma^2 = 1$. Totally 10^5 Monte Carlo runs are adopted for average.

Fig. 3 shows the BER of $x(n)$ and $b(n)$ versus prime link SNR γ_P when setting $d_0 = d_1 = d_2 = 1$ m. According to the figure, the BER of all the detectors shows a downtrend. This is because the backscatter link SNR γ_B increases with the increase of γ_P in our experiment setting, so all the detectors have satisfactory performance. It is also obvious from Fig. 3 that the suboptimal detector performs better than the LMMSE detector under both Rayleigh and Rician channels. Besides, the proposed detector obtains near-optimal performance when γ_P is less than 16 dB under the Rician channel. When γ_P >16 dB, its BER of $b(n)$ is limited by the BER of $x(n)$, and the suboptimal detector is inferior to the ML detector.



(a) BER of the PT signal $x(n)$

(b) BER of the tag signal $b(n)$

BER: bit error ratio　　LMMSE: linear minimum mean-square-error
ML: maximum-likelihood

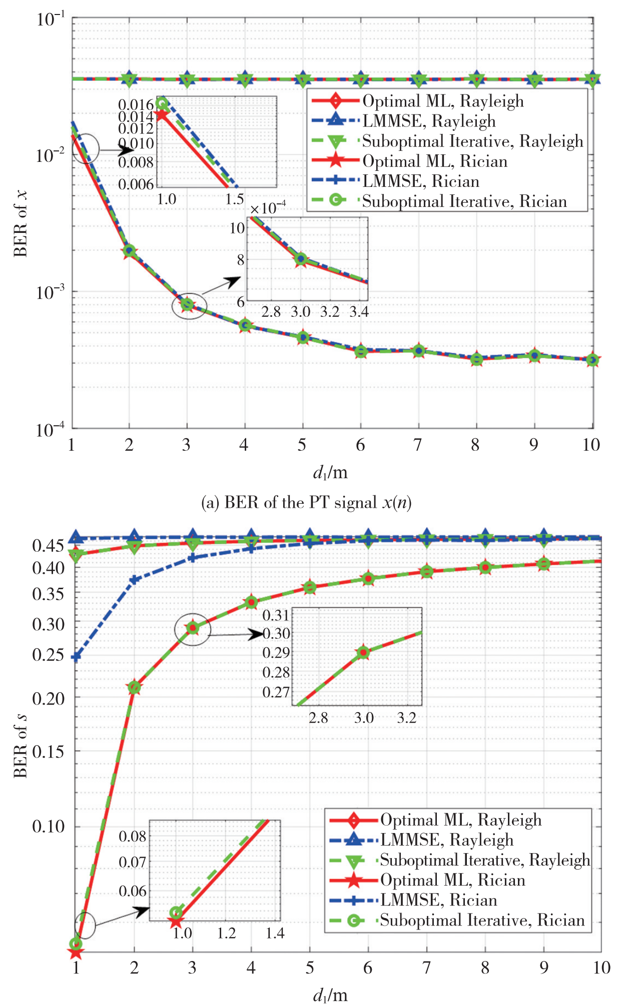
▲**Figure 3. BER of $x(n)$ and $b(n)$ versus γ_p with $d_0 = d_1 = d_2 = 1$ m**

Fig. 4 shows the BER of $x(n)$ and $b(n)$ versus d_1 when setting $\gamma_P = 8$ dB and $d_0 = d_2 = 1$ m. It is clear from the figure that the suboptimal detector and the optimal ML detector have the same performance when d_1 is greater than 2 m, and the suboptimal detector always performs better than the LMMSE detector. This proves the effectiveness of the proposed detector. We can also find that the BER of $x(n)$ decreases as d_1 gets larger while the BER of $b(n)$ increases. This is because γ_B decreases as d_1 increases. When d_1 is large enough, the backscattered signal gets too weak to be detected, so all the detectors have poor performance in detecting $b(n)$. However, as the power of the backscattered signal decreases, its inference to the prime signal alleviates, resulting in better BER performance of $x(n)$.

Fig. 5 depicts the BER performance versus γ_P in different iterations. In this figure, it is worth noting that "iteration 0" refers to step 1 in Algorithm 1. It can be found that the iteration manner can improve the detection performance under both Rayleigh and Rician channels. With the increase of γ_P, the improvement of iterative performance gets more significant, especially for the Rician channel. It can be seen that when γ_P is greater than 20 dB, the BER performance of detecting $x(n)$ and $b(n)$ increases by 79.5% and 50%, respectively. Moreover, it is clear from the figure that the curves of iteration two and iteration three are essentially indistinguishable, which proves that the performance of the suboptimal detector is stable after two iterations and is consistent with the conclusion in Ref. [19].

5 Conclusions

This paper studied the data detection problem of the SR system. First, we derived the mathematical expression of the opti-



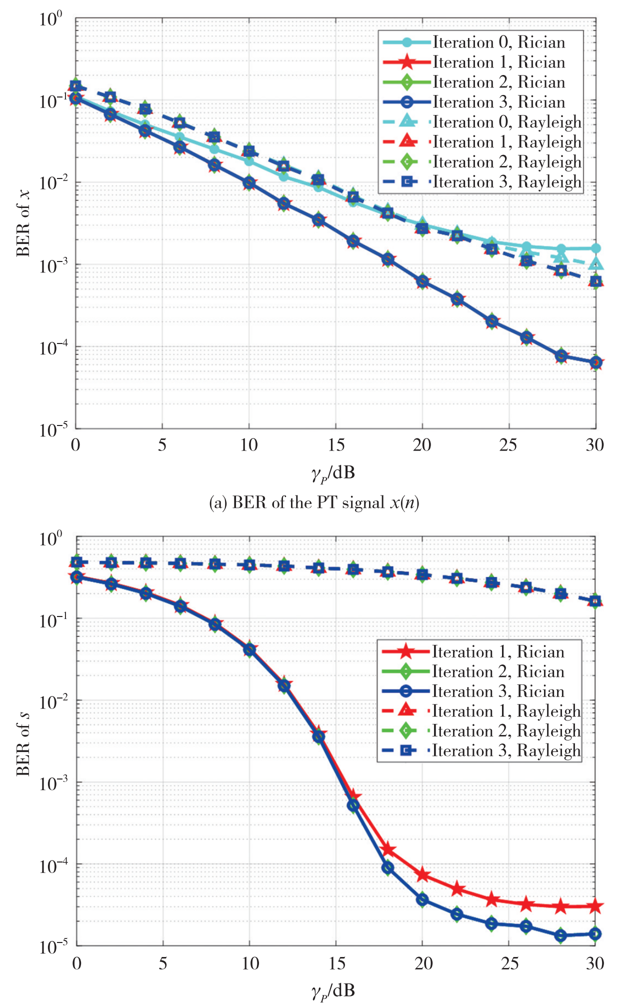
(a) BER of the PT signal $x(n)$

(b) BER of the tag signal $b(n)$

BER: bit error ratio LMMSE: linear minimum mean-square-error
ML: maximum-likelihood

▲**Figure 4. BER of $x(n)$ and $b(n)$ versus d_1 with $d_0 = d_2 = 1$ m and γ_P = 8 dB**

mal ML detector. Then, based on the fact that the power of the prime signal is much stronger than that of the backscatter signal, we therefore proposed a low-complexity suboptimal iterative detector. Numerical results showed that the proposed detector could achieve near-optimal BER performance after about two iterations.



(a) BER of the PT signal $x(n)$

(b) BER of the tag signal $b(n)$

BER: bit error ratio

▲**Figure 5. BER of $x(n)$ and $b(n)$ versus different iterations with $d_0 = d_1 = d_2 = 1$ m**

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