An Efficient Ratio Detector for Ambient Backscatter Communication

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Abstract—A challenge of ambient backscatter communication (AmBC) systems is signal recovery because the transmitted information bits are embedded in the ambient RF signals and these are unknown and uncontrollable. To meet this challenge, averaging-based energy detectors are typically used but consequently the data rate is low and there is an error floor. Here we propose a new detection strategy based on the ratio between signals received from a multiple-antenna Reader. The advantage of using the ratio is that ambient RF signals are removed directly from the embedded signals without averaging and hence it can increase data rates and avoid the error floor. Different from the original ratio detector that uses the magnitude ratio of the signals between two Reader antennas, in our proposed approach, we utilize the complex ratio so that phase information is preserved and propose an accurate linear channel model approximation. This allows the application of existing linear detection techniques from which we can obtain a minimum distance detector and closed-form expressions for bit error rate (BER). Methods for the estimation of channel state information (CSI) are also provided. In addition, coding and interleaving are also included to further enhance the BER. The results are also general, allowing any number of Reader antennas to be utilized in the approach. Numerical results demonstrate the proposed approach performs better than approaches based on energy detection and the original ratio detectors.

Index Terms—Ambient backscatter communication, channel linearization, ratio detector, energy detector, repetition code.

I. INTRODUCTION

The Internet of things (IoT) has attracted significant attention in both academia and industrial circles [1].

One approach to meet the challenge of powering IoT devices is ambient backscatter communication (AmBC) which was first proposed by Liu et al in 2013 [3]. In an AmBC system, a “Tag” harvests energy from ambient radio frequency (RF) signals to power its circuits [4], [5]. It transmits its data to a “Reader” by tuning its antenna impedance to reflect the received RF signals. Specifically, the Tag maps “0” and “1” bits to RF waveforms by adjusting the load impedance of the antenna between absorbing and reflecting states [6]. Different from conventional backscatter communication, e.g., Radio Frequency Identification (RFID), where a dedicated source of RF radiation is needed, AmBC enables battery-free Tags to communicate with other devices by harnessing ambient RF signals emitted from existing wireless systems (such as DTV [3], FM [7], [8] and Wi-Fi [9], [10], [11], [12]). Thus, AmBC can operate without any dedicated RF source or extra spectrum allocation, making it a promising approach for realizing a sustainable IoT ecosystem [2], [6], [13], [14]. In addition, the Reader does not require special duplexing circuitry (as in RFID Readers) so that existing devices, such as Wi-Fi, can potentially be modified to be Readers.

In AmBC systems, the Reader receives two types of signals: the direct link signal emitted from the ambient RF source and the signal backscattered by the Tag. The backscattered signal is much weaker than the direct link signal due to the round-trip loss [15]. In addition, the ambient RF signal is unknown and uncontrollable. Therefore, the detection of AmBC signals transmitted by the Tag is challenging [16], [17].

A. Related Work

To tackle the detection challenge of AmBC systems, averaging-based energy detection is a widely used method to recover the Tag data. The basic principle of the energy detector is to average the power of the received signal and obtain its power level, which can be thresholded for detecting Tag symbols. In [3], the feasibility of communication between two battery-free devices utilizing ambient TV signals has been shown. The bit error rate (BER) performance of the energy detector with differential encoding and maximum-likelihood (ML) detector has also been investigated [17], [18], [19]. It's function is to provide ubiquitous connectivity among a large number of small IoT computing devices (associated with people, homes, vehicles, etc) embedded in the environment and on and within people [2].
A joint energy detection scheme has been adopted where the differential coding characteristics have been exploited to avoid channel estimation and pilot symbols. The non-coherent energy detector has also been generalized to multiple-phase shift keying (MPSK) [21]. In [22], Manchester coding has been applied and an optimal non-coherent detector has been analyzed [23].

There are several disadvantages with the averaging-based energy detection approach. The first is that the averaging process significantly reduces the resulting bit rate. The detector also has a severe error floor problem due to direct link interference [24]. That is, the BER converges to a non-zero floor with increases in the ambient RF source power. Besides, energy detection generally suffers from performance loss since the averaging operation loses all phase information [15].

Due to the limitations of averaging-based energy detection, enhancements to AmBC detection techniques have also been investigated. This includes implementing multiple antennas at the Reader to improve link quality, reliability and increase data rate. In [25], [26] blind energy detectors with multi-antenna Readers have been proposed. While the BER is lowered by increasing the number of antennas, the error floor caused by energy detectors still exists. Alternative approaches have also been considered, and this includes isolating the spectrum of the backscattered and ambient RF signals [27], [28], statistical clustering [15], and statistical covariances [29].

A very different approach to remove the ambient RF background signal from the transmitted bits has also been suggested in 2014, which is based on using the ratio of signals from separate antennas at the Reader [30]. It has been demonstrated that taking the ratio of two antenna branches at the Reader can cancel the ambient RF source, allowing increases in data rate [30]. Ratio detection is particularly suited to AmBC configurations that leverage systems such as Wi-Fi and where the AmBC Reader is integrated with the Wi-Fi station. This is because the ratio detector for AmBC can straightforwardly leverage the baseband outputs and synchronization from the Wi-Fi system to form the required ratio. The idea has been further investigated by finding an approximate detection threshold and the corresponding closed-form BER expression has been derived [31]. As there is no error floor and data rates can be increased, the ratio detector approach has significant potential for further development.

## B. Contributions

In this paper, we take a new look at the AmBC Reader with ratio detection to overcome the drawbacks of conventional averaging-based energy detection. Our new contributions include:

1) Proposing a new ratio detector: Different from original ratio detectors [30], [31] that use magnitude information only, we propose using the direct ratio of the received signals so that phase information is preserved.

2) Performing channel linearization: The proposed ratio allows the development of an accurate linear channel model for the AmBC system. Based on this we simplify the ML detector to a minimum distance detector and provide a closed-form BER expression for the resulting system. The corresponding results are shown for both circularly symmetric complex Gaussian (CSCG) distributed and $M$-PSK modulated ambient RF source signals. Besides, we provide a channel state information (CSI) estimation method based on the proposed linear channel model, which is shown to have low complexity and good accuracy.

3) Proposing coding and interleaving techniques: With the proposed accurate linear channel model, commonly-used linear techniques such as coding and interleaving can be straightforwardly implemented, which is shown to further enhance detection performance.

4) Generalizing to more than two antenna systems: When more than two Reader antennas are utilized, we describe a ratio selection approach that reduces the BER further.

In Section II, the system model of the proposed AmBC system is provided. In Section III, we introduce our proposed ratio detector with our accurate linear channel approximation, minimum distance detector, exact closed-form BER expressions and CSI estimation. Section IV introduces coding and interleaving while Section V generalizes the approach to arbitrary numbers of antennas. Section VI provides simulation results, and conclusions and suggestions for future work are provided in Section VII.

**Notation:** Bold lower and upper case letters denote vectors and matrices, respectively. A symbol not in bold font represents a scalar. $x^*$, $\Re \{x\}$, and $|x|$ refer to the conjugate, real part, and modulus, respectively, of a complex scalar $x$. $x^T$ and $|x|^2$ refer to the transpose and the $l_2$-norm of a vector $x$. $\text{diag}(x)$ returns a square diagonal matrix with the elements of vector $x$ on the main diagonal. $X^T$ refers to the transpose of a matrix $X$. $\mathbb{C}^{M \times N}$ denotes the space of $M \times N$-dimensional complex matrices. $\mathcal{CN}(0, \sigma^2)$ refers to the CSCG distribution with zero mean and variance $\sigma^2$, $f(\cdot)$ denotes the PDF of a random variable and $\Pr(\cdot)$ denotes the probability of an event. $Q(\cdot)$ refers to the Q-function.

## II. System Model

Consider an AmBC system consisting of an ambient RF source, a passive Tag equipped with a single antenna, and a Reader equipped with $Q$ antennas as shown in Fig. 1. The ambient RF signal is denoted by $s(n)$ (with symbol period $T_a$), where $n = 1, 2, \ldots$ is the sample index of the ambient source. $s(n)$ is assumed random (and may arise from different RF sources) and follows a CSCG distribution with zero mean and variance $\sigma^2$. $f(\cdot)$ refers to the PDF of a random variable and $\Pr(\cdot)$ denotes the probability of an event. $Q(\cdot)$ refers to the Q-function.

$$z_q(n) = (A_{SR}h_{q}^{SR} + \alpha A_{TR}A_{ST}h_{q}^{TR}h_{q}^{ST}x) s(n) + w_q(n),$$

(1)

where $A_{TR}$ and $h_{q}^{TR}$ denote the large- and small-scale channel fading between the Tag antenna and the $q$th Reader antenna, $A_{ST}$ and $h_{q}^{ST}$ denote the large- and small-scale channel fading between the ambient RF source and the Tag antenna, $A_{SR}$ and $h_{q}^{SR}$ denote the large- and small-scale channel fading between the ambient RF source and the $q$th Reader antenna. The symbol
transmitted by the Tag antenna is denoted as $x$, and $w_q(n)$ is the additive white Gaussian noise (AWGN) at the $q$th Reader antenna. $\alpha$ denotes the hardware implementation loss of the Tag. We assume block-fading, where the channel coherence time exceeds the transmission duration of a block. However, the channel will still vary from one block to another because multi-path components are varying over time [32]. Due to the short Tag-to-Reader distance in practice, the channel between the Tag and Reader can be assumed to have a single path, and therefore the inter-symbol-interference (ISI) can be neglected [33], [34].

It should be noted that the backscattered signal is composed of two different components: structure and antenna mode scattering [35]. The former is generated when the antenna has a perfect impedance match and is always present, and the latter is due to the mismatch between the load and the matched impedance [36]. The effect of structure mode scattering can be absorbed into the direct link channel in channel modeling [15], [32].

We assume $h_{SR,q}^*, h_{TR,q}^*$, and $h_{ST}$ are independent and identically distributed (i.i.d.), quasi-static, and frequency flat. We also assume $A_{SR} \approx A_{ST}$ since the Tag and the Reader are close to each other (such as logistics management, on-body sensors, smart homes). Therefore, we can normalize (1) by $A_{SR}$ and rewrite (1) as

$$z_q(n) = (h_{SR}^* + h_{TR}^* gx) s(n) + \bar{w}_q(n),$$

where we define $z_q(n) = z_q(n) / A_{SR}$, $g = \alpha A_{TR} h_{ST}$, and $\bar{w}_q(n) = w_q(n) / A_{SR}$. We assume $\bar{w}_q(n) \sim \mathcal{CN}(0, N_w)$ where $N_w$ denotes the normalized noise power.

Leveraging (2), we can define the direct link SNR $\gamma_d$ as

$$\gamma_d = \frac{P_s}{N_w},$$

which is the ratio of ambient RF signal power and normalized noise power at the Reader. This is referred to as SNR in the remainder of the paper. We also define a relative SNR $\Delta \gamma$ as

$$\Delta \gamma = \alpha^2 A_{TR}^2,$$

which is the ratio of the signal power from the backscatter link and the direct link. The relative SNR $\Delta \gamma$ is usually lower than $-30$ dB and therefore special techniques need to be utilized for AmBC signal detection [37].

The most common detection approach in AmBC is averaging-based energy detection but it suffers from performance issues as discussed earlier. As an alternative approach, it is possible to consider the ratio between two antenna branches (say $q = 1$ and 2) as it can effectively cancel or divide out the unknown ambient RF source signal $s(n)$. Not only can this overcome the error floor of conventional averaging-based energy detection, it can also increase the data rate. The originally proposed ratio detector uses the magnitude ratio of the received signals at two antenna branches [30], [31]. It is shown that the ratio detector avoids the error floor phenomenon faced by the averaging-based energy detector [31], with the data rate and communication range having been greatly improved [30]. However, taking the magnitude ratio loses potentially useful phase information, and also makes the channel model nonlinear. In [30], it is pointed out that the use of magnitudes allows the use of non-coherent receivers. However, with AmBC Readers being integrated in systems such as Wi-Fi, signals received by different antenna branches will be phase coherent due to the use of a single local oscillator. This allows the consideration of complex signal ratios. An advantage of using complex ratios is that an accurate linear channel model can be developed for AmBC as shown next.

### III. PROPOSED RATIO DETECTOR

We firstly analyze the system performance of the ratio detector with $Q = 2$ antenna branches to highlight its functionality. Later in Section V we provide a straightforward generalization for $Q > 2$ antennas.

We denote the signal ratio between the two antenna branches ($q = 1, 2$) as

$$\lambda(n) = \frac{\bar{z}_1(n)}{\bar{z}_2(n)} = \frac{(h_{SR}^* + h_{TR}^* gx) s(n) + \bar{w}_1(n)}{(h_{SR}^* + h_{TR}^* gx) s(n) + \bar{w}_2(n)}.$$  (5)

This is different from the originally proposed ratio detector as we have removed the magnitude or modulus operation. The advantage of using this ratio is that it allows us to develop an accurate linear channel model for the AmBC system. Subsequently, the use of linear detectors, and coding can be utilized.

One issue in forming the ratio (5) is retaining its phase. However, proposed AmBC Readers are likely to be integrated with existing wireless systems such as Wi-Fi. In these circumstances, the system will be coherent and phase coherence will exist between antenna branches. Therefore, extracting the I and Q signals for each antenna branch and taking the ratio will not likely require additional information. This is a significant advantage of using this ratio.

#### A. PDF and ML Detection

In this paper, for simplicity we focus on using BPSK modulation for the transmit signal $x$, that is, $x = \pm 1$. Other common modulation techniques such as ASK, PSK and QAM, can also be applied in the proposed ratio detector. Defining $\mu_q = h_{SR}^* + h_{TR}^* gx$, $q = 1, 2$, as the composite channel between the Reader and Tag when $x = \pm 1$ allows us to write

$$\mu_q s(n) + \bar{w}_q(n) \sim \mathcal{CN}(0, \sigma_q^2)$$

where $\sigma_q^2 = |\mu_q|^2 P_s + N_w$, $q = 1, 2$.
Since \( \lambda(n) \) is a ratio of two CSCG distributed random variables, according to [38] and [39], its PDF is given by
\[
f(\lambda) = \frac{1 - |\rho|^2}{\pi \sigma_1^2 \sigma_2^2} \left( \frac{|\lambda|^2}{\sigma_1^2} + \frac{1}{\sigma_2^2} - 2 \rho \lambda - \rho_1 \lambda \right)^{-2},
\]
where \( \lambda_r \) and \( \lambda_i \) represent the real and imaginary parts of \( \lambda \), respectively; \( \rho \), \( \rho_1 \), and \( \rho_2 \) represent the real and imaginary parts, respectively, of \( \rho \), which is the complex correlation coefficients between \( z_1(n) \) and \( z_2(n) \) and is written as
\[
\rho = \frac{\mu_1 \mu_2 P_s}{\sigma_1 \sigma_2}.
\]
In ML detection, the goal is to design an optimal detector that can minimize the error probability, or equivalently, maximize the correct decision probability
\[
\hat{x} = \arg \max_{x \in \{-1, 1\}} Pr(x | \lambda).
\]
Since the transmit messages \( x = -1 \) and \( x = 1 \) are equiprobable, according to Bayes’ theorem, the ML criterion is written as
\[
\hat{x} = \begin{cases} 
-1, & \text{if } f(\lambda | x = -1) \geq f(\lambda | x = 1) \\
1, & \text{if } f(\lambda | x = -1) < f(\lambda | x = 1).
\end{cases}
\]
To obtain \( f(\lambda | x) \), we first need to estimate the ambient signal’s power \( P_s \) and the normalized noise level \( N_w \). \( N_w \) can be obtained from the Reader’s noise performance or noise figure, and \( P_s \) can be estimated by measuring the average received ambient signal’s power when the Tag does not transmit data. The direct link SNR can also be obtained in this way. Additionally, we also need to estimate all the channel parameters \( g, h_{SR}^{TR}, \) and \( h_{SR}^{Q}, q = 1, 2 \) individually. Once these parameters are estimated, \( \mu_q, \sigma_q, \) and \( \rho \) conditioned on \( x \) can be calculated. Then \( f(\lambda | x) \) can be found using (6), and the transmit message \( x \) is determined by comparing the size relationship of two posterior density functions.

The optimal ML detector is computationally intricate due to two reasons. Firstly, it needs to compute intricate PDFs, resulting in a large decoding delay, and determining a signal threshold for detection is also difficult. Secondly, prior knowledge of ambient RF sources and channels is needed. However, estimating \( P_s \) and \( N_w \) is possibly inaccurate and it is challenging to estimate all the channel parameters individually, which leads to high estimation complexity. It should also be noted that the ML detector relies on knowing the exact distribution of the ambient RF source, which is difficult for the Reader to access. The intricacy of ML detection can be completely avoided by utilizing a different approach. It is shown next that the channel model (5) can be accurately approximated by a linear channel model under the conditions of AmBC. This allows us to devise a straightforward minimum distance detector which is more robust to the ambient RF sources, and enables us to develop a channel estimation method with low complexity and good accuracy. In addition, it opens up the use of all of the linear detection tools available such as coding, interleaving, and selection diversity.

### B. Linearization of Proposed Ratio Detector

Utilizing the complex ratio (5), we develop an accurate channel linearization for AmBC. We rewrite the ratio \( \frac{z_1(n)}{z_2(n)} \) as
\[
\frac{z_1(n)}{z_2(n)} = \frac{h_{SR}^{TR} g x}{h_{SR}^{Q} s(n)}.
\]
Taking logarithms we have
\[
\log \left( \frac{z_1(n)}{z_2(n)} \right) = \log \left( \frac{h_{SR}^{TR}}{h_{SR}^{Q} s(n)} \right).
\]
Under the condition AmBC conditions, the direct link (ambient RF source to Reader) has a significantly higher channel gain than the indirect link (ambient RF source to Tag and then backscattered to Reader). This corresponds to the fact that the relative SNR \( \Delta \gamma \) in practical AmBC systems is usually lower than \(-30 \text{ dB} \) [37]. Therefore, with \( q = 1, 2 \), the signals very frequently satisfy
\[
|h_{q}^{TR} g x| \ll |h_{SR}^{Q} s(n)|, \quad |\bar{w}_q(n)| \ll |s(n) h_{SR}^{Q}|.
\]
Under these conditions it can be readily seen that
\[
\frac{h_{q}^{TR} g x}{h_{SR}^{Q} s(n)} + \frac{\bar{w}_q(n)}{h_{SR}^{Q} s(n)} \rightarrow 0.
\]
Using the limit that \( \log (1 + x) \rightarrow x \) when \( x \rightarrow 0 \) and the property (14), we have
\[
\log \left( 1 + h_{q}^{TR} g x + \frac{\bar{w}_q(n)}{h_{SR}^{Q} s(n)} \right) \rightarrow \frac{h_{q}^{TR} g x}{h_{SR}^{Q} s(n)} + \frac{\bar{w}_q(n)}{h_{SR}^{Q} s(n)}.
\]
Thus, (11) can be expressed as
\[
\log \left( \frac{z_1(n)}{z_2(n)} \right) = \log \left( \frac{h_{SR}^{TR}}{h_{SR}^{Q} s(n)} \right) + \left( \frac{h_{q}^{TR} g x}{h_{SR}^{Q} s(n)} - \frac{\bar{w}_q(n)}{h_{SR}^{Q} s(n)} \right) \frac{1}{s(n)}.
\]
As the constant bias term \( \log \left( \frac{h_{SR}^{TR}}{h_{SR}^{Q} s(n)} \right) \) in (16) can be estimated and removed and the details will be shown in subsection E. Let us define \( \hat{g} \equiv \log \left( \frac{z_1(n)}{z_2(n)} \right) - \log \left( \frac{h_{SR}^{TR}}{h_{SR}^{Q} s(n)} \right) \); according to (16), we can obtain
\[
\hat{g} = h x + \bar{w},
\]
where \( h \) is defined as
\[
h \triangleq \left( \frac{h_{q}^{TR}}{h_{SR}^{Q}} - \frac{\bar{w}_q(n)}{h_{SR}^{Q} s(n)} \right) g.
\]
and \( \hat{w} \) is defined as

\[
\hat{w} = \left( \frac{\hat{w}_1(n)}{h_1^{SR}} - \frac{\hat{w}_2(n)}{h_2^{SR}} \right) \frac{1}{s(n)}.
\]  

Note that \( \left( \frac{\hat{w}_1(n)}{h_1^{SR}} - \frac{\hat{w}_2(n)}{h_2^{SR}} \right) \) still follows a CSCG distribution, so \( \hat{w} \) is a ratio of two CSCG variables. According to [38], the PDF of \( \hat{w} \) can be obtained as

\[
f(\hat{w}) = \frac{N_w}{\pi P_s} \left( \frac{1}{|h_1^{SR}|^2} + \frac{1}{|h_2^{SR}|^2} \right) \cdot \left( |\hat{w}|^2 + \frac{1}{|h_1^{SR}|^2} + \frac{1}{|h_2^{SR}|^2} \right)^{-2}.
\]

A further detail is that herein we only take the principal value of each logarithm. As a result, the phase of \( \log \left( \frac{\bar{z}_1(n)}{\bar{z}_2(n)} \right) \) is restricted to \((-\pi, \pi)\) while the right-hand side of (11) has a phase in \((-3\pi, 3\pi)\). Since the principal value of a product of two complex numbers \( ab \) can be expressed by \( \log(|ab|) + \arg(ab) \cdot \pi = \log(|a|) + \log(|b|) + \arg(a) \cdot \pi + \arg(b) \cdot \pi + 2n\pi \), \( n \in \mathbb{Z} \), it is possible that the phase of the right-hand side of (11) has \( \pm 2\pi \) shift from \( \log \left( \frac{\bar{z}_1(n)}{\bar{z}_2(n)} \right) \). Consequently, (17) does not always hold. Thus, we cannot utilize (17) directly to detect the Tag data since the phase shift will decrease the detection performance. In order to reduce its influence, we propose a phase compensation method.

Recall that the direct link has a significantly higher channel gain than the indirect link. Thus \( \log \left( \frac{h_1^{SR}}{h_2^{SR}} \right) \) is dominant in \( \log \left( \frac{\bar{z}_1(n)}{\bar{z}_2(n)} \right) \) and we can compare the phase of them to reveal if there is a \( 2\pi \) phase shift. It should be noted that after taking the logarithm of the received signal ratio, the compensated phase should be added to \( \hat{y} \). After removing the bias \( \log \left( \frac{h_1^{SR}}{h_2^{SR}} \right) \), the extra phase \( \Delta \phi \) that needs to be compensated on \( \hat{y} \) is

\[
\Delta \phi = \begin{cases} 
2\pi, & \text{if } \phi \left( \log \left( \frac{\bar{z}_1(n)}{\bar{z}_2(n)} \right) \right) \cdot \pi - \phi \left( \log \left( \frac{h_1^{SR}}{h_2^{SR}} \right) \right) < -\pi \\
-2\pi, & \text{if } \phi \left( \log \left( \frac{\bar{z}_1(n)}{\bar{z}_2(n)} \right) \right) \cdot \pi - \phi \left( \log \left( \frac{h_1^{SR}}{h_2^{SR}} \right) \right) > \pi \\
0, & \text{otherwise},
\end{cases}
\]

(21)

where \( \phi \left( \log \left( \frac{\bar{z}_1(n)}{\bar{z}_2(n)} \right) \right) \) and \( \phi \left( \log \left( \frac{h_1^{SR}}{h_2^{SR}} \right) \right) \) represent the phase of \( \log \left( \frac{\bar{z}_1(n)}{\bar{z}_2(n)} \right) \) and \( \log \left( \frac{h_1^{SR}}{h_2^{SR}} \right) \), respectively.

The modified (17) is then written as

\[
y = \hat{y} + J\Delta \phi = hx + \hat{w},
\]

(22)

which is the finalized linear channel model for the proposed ratio detector.

In this paper, we focus on single-antenna Tag’s, however, it should be noted that our proposed linear channel model can easily generalize to multi-antenna Tag. Consider a passive Tag equipped with \( P \) antennas, the normalized received signal at \( q \)th Reader antenna (2) can be rewritten as

\[
\bar{z}_q(n) = \left( h_q^{SR} + h_q^{TR} \right) G s(n) + \hat{w}_q(n),
\]

where we define \( h_q^{TR} = \left[ h_{q,1}^{TR}, \ldots, h_{q,p}^{TR}, \ldots, h_{q,P}^{TR} \right] \), \( G = \alpha A_R \text{diag} \left( h_1^{ST}, \ldots, h_p^{ST}, \ldots, h_P^{ST} \right) \), and the transmit signal \( \mathbf{x} = [x_1, \ldots, x_p]^T \). \( x_p \) refers to the symbol transmitted by the \( p \)th Tag antenna using backscattering, and \( h_{q,P}^{TR} \) denotes the small-scale channel fading between the \( p \)th Tag antenna and the \( q \)th Reader antenna. After taking the ratio of \( \bar{z}_1(n) \) and \( \bar{z}_2(n) \) and performing steps (10)–(21), the linear channel model can be written as

\[
y = \left( \frac{h_1^{TR}}{h_1^{SR}} - \frac{h_2^{TR}}{h_2^{SR}} \right) Gx + \hat{w}.
\]

In summary, by performing the logarithm approximation (16), removing bias, and compensating phase shift (21), we can approximate the ratio channel model in AmBC (5) as a linear channel model (22). This channel model approximation is accurate for most practical configurations in AmBC as shown later in Section VI.

C. Minimum Distance Detector

The computational complexity of the optimal ML detector (9) can be reduced by leveraging the linearized AmBC channel model to simplify the detection process.

For simplicity, we further define \( \tau \) as

\[
\tau = \left( \frac{1}{|h_1^{SR}|^2} + \frac{1}{|h_2^{SR}|^2} \right) \frac{N_w}{\pi P_s}.
\]

(25)

The ML detector is then given by

\[
\hat{x} = \arg \max_{x \in \{-1, 1\}} f(y | x) = \arg \max_{x \in \{-1, 1\}} \tau \left( |y - hx|^2 + \pi \tau \right)^{-2}.
\]

(26)

It can be readily checked that the function to be maximized in (26) is monotonically decreasing with \( |y - hx|^2 \). Thus (26) can be simplified as

\[
\hat{x} = \arg \min_{x \in \{-1, 1\}} |y - hx|^2,
\]

(27)

where \( h \) is given by (18). It implies that the ML detector (9) can be reduced to a minimum distance detector.

The detection analysis above is based on the assumption that the ambient RF signal follows a CSCG distribution. However, in reality, the ambient RF symbols may follow a specific constellation, e.g., M-PSK. In the following we will show that based on the proposed linear channel model (22), no matter the ambient RF signal is CSCG distributed or M-PSK modulated, the minimum distance detector (27) provides the optimum performance.

Suppose \( s(n) \) is selected from a constellation set \( S = \{s_1, s_2, \ldots, s_M\} \) with average power \( P_s \) and the backscatter symbol is BPSK modulated with \( x \in \{-1, x_2 = -1\} \). Since the RF source and the Tag select transmitted symbols uniformly and randomly from the constellation sets, based on the linear channel model (22), the received signal has the PDF [40]

\[
f(y) = \frac{1}{2M} \sum_{i=1}^{2} \sum_{m=1}^{M} \frac{1}{\pi \left( \frac{1}{|h_1^{SR}|^2} + \frac{1}{|h_2^{SR}|^2} \right)} \frac{N_w}{|\sigma_m|^2}.
\]
BER analysis for the proposed minimum distance detector.

\[ D. \text{BER Analysis} \]

Section VI.

Reduced without a reduction in performance as shown in (6). There-

equal to the linear channel model with the coherent

\[ \text{It is shown that the LR detector, while providing better} \]

\[ \text{performance, is not immediately suitable for AmBC systems.} \]

\[ \text{To conclude, based on the proposed linearized AmBC chan-
\[ \text{nel model (22), we can apply linear detection to detect} \]

\[ \text{It implies that the ML detector also can be reduced to} \]

\[ \text{a minimum distance detector if the ambient RF signal is} \]

\[ \text{M-PSK modulated, which is the same as the linear detector} \]

\[ \text{when the ambient RF source is CSCG distributed. Besides,} \]

\[ \text{the decision rule is independent of the number of constellation} \]

\[ \text{points of the ambient RF signal. This observation demonstrates} \]

\[ \text{the robustness of our minimum distance detector due to the} \]

\[ \text{use of our linear channel model.} \]

\[ \text{It is also interesting to compare the minimum distance} \]

\[ \text{detector based on the linear channel model with the coherent} \]

\[ \text{likelihood-ratio (LR) detector proposed in [15], [24], and [32],} \]

\[ \text{that provides optimal detection performance. In the Appendix} \]

\[ \text{it is shown that the LR detector, while providing better} \]

\[ \text{performance, is not immediately suitable for AmBC systems.} \]

\[ \text{To conclude, based on the proposed linearized AmBC chan-
\[ \text{nel model (22), we can apply linear detection to detect} \]

\[ \text{and avoid computing the complicated PDF functions (6). There-
\[ \text{fore, the computational complexity for detection is greatly} \]

\[ \text{reduced without a reduction in performance as shown in} \]

\[ \text{Section VI.} \]

\[ \text{D. BER Analysis} \]

Utilizing the linear AmBC channel model, we can provide BER analysis for the proposed minimum distance detector.

Suppose we transmit \( x \) in a single transmission and the ambient RF source is CSCG distributed. According to (27), the error event is the distance between the received signal \( y \) and \( hx \) is larger than \(-hx\). Equivalently,

\[ |y - hx|^2 > |y + hx|^2; \]

in other words,

\[ \Re \{hx \hat{w}\} < -|h|^2. \]

Let \( \varphi = hx \hat{w} \), and \( \varphi_r \) and \( \varphi_i \) represent the real and imaginary parts, respectively, of \( \varphi \). It can be readily seen that \( \varphi \) is also a ratio of CSCG variables. Thus, the error probability can be expressed as

\[ P_b = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\varphi) \, d\varphi_r \, d\varphi_r, \]

where

\[ f(\varphi) = \tau |h|^2 \left( \varphi_r^2 + \varphi_i^2 + \pi \tau |h|^2 \right)^{-2}. \]

To obtain the closed-form expression of \( P_b \), the indefinite integral of \( f(\varphi) \) should be found. In [38], it is pointed out that the integral of the PDF (33) can be expressed in closed-form as

\[ \int \int f(\varphi) \, d\varphi_r \, d\varphi_r = \zeta(\varphi_r, \varphi_i) + \zeta(\varphi_i, \varphi_r) = G(\varphi_r, \varphi_i), \]

where

\[ \zeta(\varphi_r, \varphi_i) = \frac{\gamma(z_i)}{2\pi} \cdot \arctan \left( \frac{\varphi_r}{\sqrt{\pi \tau |h|^2 + \varphi_i^2}} \right), \]

and

\[ \gamma(z_i) = \frac{\varphi_i}{\sqrt{\pi \tau |h|^2 + \varphi_i^2}}. \]

The BER \( P_b \) is therefore expressed as

\[ P_b = G\left(-|h|^2, \infty\right) + G\left(-\infty, -\infty\right) - G\left(-|h|^2, -\infty\right) - G\left(-\infty, -\infty\right), \]

where the function \( G \) is given by (34).

Substituting (34) in (37), we obtain a closed-form BER expression as

\[ P_b = \frac{1}{\pi^2 \tau |h|^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp \left( -\frac{\varphi_r^2 + \varphi_i^2}{\pi \tau |h|^2} \right) \, d\varphi_r \, d\varphi_r, \]

which is independent of the number of constellation points of the ambient RF signals.

It can be seen that, by using the approximate linear channel model, exact closed-form BER expressions can be found, which again shows the benefit of channel linearization. Since we leverage the phase information, it can be expected that (38) has lower BER than the original ratio detector. The BER performance of the detectors are numerically compared in Section VI.

\[ E. \text{Channel Estimation Method} \]

To coherently decode the backscatter symbols in our proposed ratio detector, CSI is needed at the Reader. Estimating CSI is challenging in AmBC because the ambient RF source cannot be controlled. However, in our approach, since a linear channel model has been constructed (22), conventional channel estimation methods can be implemented.

To coherently detect the received signal using (22), both the bias \( b \triangleq \log(h_{1n}^{SR}/h_{2n}^{SR}) \) and the channel \( h \) should be estimated. To this end, a training signal, a priori known at the
Reader, is transmitted at the start of a new block transmission from the Tag. The Reader then employs an optimization procedure based on least-squares (LS) estimation.

Specifically, for a channel estimation process within the channel coherence time, two training symbols $u_1$ and $u_2$ are sequentially transmitted by the Tag. At the Reader side, the received training signal over the two symbol periods is given by

$$
\begin{bmatrix}
y_1 \\
y_2
\end{bmatrix} =
\begin{bmatrix}
u_1 & 1 \\
u_2 & 1
\end{bmatrix}
\begin{bmatrix}
h \\
b
\end{bmatrix} +
\begin{bmatrix}
\tilde{w}_1 \\
\tilde{w}_2
\end{bmatrix}.
$$

(40)

Denoting $y = [y_1, y_2]^T$, $U = [u_1, 1; u_2, 1]$, and $\hat{h} = [h, b]^T$, the Reader estimates the channel using LS as

$$
\hat{h}^{LS} = \arg \max_{\hat{h} \in \mathbb{C}^2} \| y - U\hat{h} \|^2_2.
$$

(41)

According to [41], the estimated $\hat{h}^{LS}$ is given by

$$
\hat{h}^{LS} = (U^H U)^{-1} U^H y.
$$

(42)

Taking $u_1 = 1$ and $u_2 = 0$ and substituting $U$ to (42), we obtain

$$
\hat{h}^{LS} =
\begin{bmatrix}
y_1 - y_2 \\
y_2
\end{bmatrix} =
\begin{bmatrix}
h \\
b
\end{bmatrix} +
\begin{bmatrix}
\tilde{w}_1 - \tilde{w}_2 \\
\tilde{w}_2
\end{bmatrix}.
$$

(43)

Thus, $y_2$ can be viewed as an estimate of bias $b$, and $y_1 - y_2$ can be viewed as an estimate of channel $h$. Following the conventional LS estimation process, by repeatedly transmitting the two training symbols $u_1$ and $u_2$ (e.g., each for $N$ times), we can form the matrix $\Phi = [U; U; \ldots; U] \in \mathbb{C}^{2N \times 2}$, so that the estimation error can be averaged and minimized. The corresponding averaged estimated $\hat{h}^{LS}$ is then given by

$$
\hat{h}^{LS} = (\Phi^H \Phi)^{-1} \Phi^H y.
$$

(44)

According to (43) and (44), it can be seen that by backscattering bit “1” and “0” repeatedly $N$ times each, the bias $b$ can be estimated by averaging the $N$ samples of $y_2$, and the channel $h$ can be estimated by averaging the $N$ samples of $y_1 - y_2$.

The whole channel estimation process at the Reader can be summarized as follows: during the channel coherence time, backscatter bit “1” for $N$ times and then bit “0” for $N$ times. Averaging the $N$ received samples related to bit “0” ($y_2$), the result is the estimate of bias $b$. Averaging the $N$ samples of $y_1 - y_2$, the result is the estimate of channel $h$.

If we assume the channel coherence time is 500 $\mu$s and the bandwidth is 40 MHz then 20000 symbols can be sent. Therefore, with $N = 1000$, the proportion of training in the transmission block is 10%. Besides, it can be seen that our channel estimation method has reasonably low complexity at the Reader side since only averaging and subtraction need to be performed. At the Tag side, transmitting a training sequence “0” is equivalent to the Tag being silent, and transmitting a training sequence “1” represents Tag backscattering. The training sequence transmission can also be used for synchronization. Since our system is backscattering, the training process does not require additional power for transmission since the “0” and “1” can be held continuously to create the required repetition.

IV. CODING AND INTERLEAVING

While the previous results can be utilized directly to achieve AmBC with high data rates, the strong interference from the direct link limits performance. To overcome this challenge, coding and interleaving are further combined with the proposed ratio detector. The formulations and advantages of this approach are detailed next.

Due to the development of the linear channel model (22), it is possible to implement channel coding techniques to enhance the performance. However, to achieve the necessary gain in performance required, we need to select very low coding rates such as 1/500 or lower. Therefore, conventional codes as used in terrestrial communications cannot be utilized. For this reason, we utilize the conventional repetition code with very low coding rates to leverage time diversity to enhance BER performance. To further combat deep fading, interleaving is combined with the repetition code. During interleaving, the transmitted data is arranged over multiple code blocks by the interleaver before backscattering. Due to this, the block experiencing deep fading is spread out among multiple blocks. When the Reader rearranges the blocks, the errors appear as independent random errors with short lengths, and are easier to detect [42], [43].

The expansion duration, or repetition length is taken as $K$ symbols. It is assumed the channel coherence time is $C$ symbols. We assume that an arbitrary incoming bit stream at the Tag is written as $x_1, x_2, \ldots$, and the bits are independent. Consider an arbitrary single bit $x_c$ whose duration is expanded $K$ times to form a transmit vector $x_c = [x_c; x_c; \ldots; x_c]$ of dimension $K$. Collecting $c$ for 1 to $C$, we form a block $X$ as $X = [x_1, x_2, \ldots, x_C]$. Applying interleaving, $X$ is rearranged using a transpose operation as $V = X^T = [v_1, v_2, \ldots, v_K]$, where $v_k = [x_1; x_2; \ldots; x_C]$ is a C dimensional vector representing the transmitting bit stream during the $k$th block time. Now each repetition codeword is rearranged into $K$ blocks.

At the Reader side, after channel linearization, the received signal matrix during $K$ coherent time slots is given by

$$
Y = V \text{diag}(h) + W = [y_1, y_2, \ldots, y_K],
$$

where $h = [h_1; h_2; \ldots; h_K]$ denotes the channel vector of $K$ blocks and $h_k$ denotes the $k$th realization of channel $h$. $W$ is the noise matrix where $\tilde{w}_{c,k}$ represents the noise of the $c$th received signal in the $k$th block. It can be seen that $x_c$ experiences $K$ channels during interleaving, which offers channel diversity to help detect the signal.

A deinterleaver is used to recover each repetition code. After rearranging the received matrix $Y$, we have

$$
R = Y^T = [r_1, r_2, \ldots, r_C],
$$

where $r_c = [r_{c,1}; r_{c,2}; \ldots; r_{c,K}] = [h x_c + w_c; \ldots; h x_c + w_c]$, with $w_c = [\tilde{w}_{c,1}; \tilde{w}_{c,2}; \ldots; \tilde{w}_{c,K}]$ representing the noise vector. Since each repetition code is independent, we can use $r_1$ to $r_C$ to decode $x_1$ to $x_C$. It can be seen that for each Tag symbol $x_c$, after repeated encoding and interleaving, the Reader receives vector $r_c$, which includes $K$ different received copies experiencing different channels and noises. Utilizing these copies, majority voting can be utilized to detect $x_c$ [44].
Algorithm 1 Optimal Ratio Selection Scheme

Initialize: Channel parameters $h_q^\text{SR}$, $h_q^\text{ST}$, $q \in \{1,2,\ldots,Q\}$. 

\textbf{eta} is sufficiently large.

1: \textbf{for} $j = 2 : Q$
2: \hspace{1em} \textbf{for} $i = 1 : j - 1$
3: \hspace{2em} \text{Calculate $\eta_{i,j}$ using (47)}
4: \hspace{2em} \text{if} $\eta_{\text{min}} \geq \eta_{i,j}$
5: \hspace{3em} Update $\eta_{\text{min}}$ by $\eta_{i,j}$
6: \hspace{2em} \textbf{end}
7: \hspace{1em} \textbf{end}
8: \textbf{end}
9: \text{Select antenna} $i,j$ according to $\eta_{\text{min}}$
10: \text{Calculate the optimal ratio} $\lambda_{\text{opt}} = z_i(n) / z_j(n)$

\textbf{Return} $\lambda_{\text{opt}}$

It can be seen that since interleaving is utilized, each Tag symbol can experience different channels, and this channel diversity can significantly lower BER, which will be verified in Section VI. It should be noted that the channel vector $h$ is obtained based on the proposed linear channel model, without which the detection process will be difficult to implement.

V. OPTIMUM RATIO SELECTION SCHEME

In this section, we generalize the ratio detector to Readers with $Q > 2$ antennas. With $Q > 2$ Reader antennas, there are a variety of ratios that can be considered, as well as many methods to utilize them. For example, the ratio need not be the straightforward ratio of a pair. The resulting ratios can also be combined in various ways including some form of maximal ratio combining. The full investigation of detectors for dealing with $Q > 2$ receive antennas can therefore be seen to be a significant undertaking.

To demonstrate the potential of our proposed ratio detector, and coding and interleaving techniques with $Q > 2$, we restrict our approach to the most straightforward system and leave the investigation of the complete generalization to future work. As such we restrict the ratios to be between pairs of antenna branches and then propose an optimal ratio selection scheme to leverage selection diversity. The ratio selection scheme has a straightforward design which leads to lower decoding complexity and delay. Besides, compared with other combining schemes such as maximal ratio combining which needs $Q$ RF chains, the ratio selection scheme only needs two RF chains, reducing cost, complexity, power consumption, and size of the Reader [45], [46]. Even this straightforward approach provides good improvements in performance as shown later in the simulation results section.

Here we take the CSCG distributed ambient RF signals as an example. Our goal is to select the optimal ratio to minimize the BER (38). Accordingly, the optimization problem can be formulated as

$$\textbf{P1}: \min_{i,j} \frac{1}{2} - \frac{1}{2 \sqrt{\tau_{i,j}^2 + 1}}$$

s.t. $i,j \in \{1,2,\ldots,Q\}, i \neq j$ (45)

where $\tau_{i,j}$ and $h_{i,j}$ represent the value of $\tau$ and $h$ calculated with the $i$th and $j$th antenna pairs, $i,j \in \{1,2,\ldots,Q\}, i \neq j$.

To solve this problem, we first observe that $P_t$ monotonically increases with $\eta_{i,j}$, which is given by

$$\eta_{i,j} = \frac{\pi P_t}{N_w} \frac{|g|^2}{|h_{i,j}|^2}$$

$$\tau_{i,j} = \frac{1}{|h_{i,j}^\text{SR}|} + \frac{1}{|h_{i,j}^\text{ST}|}$$

$$\eta_{i,j} = \frac{\pi P_t}{N_w} \frac{|g|^2}{|h_{i,j}|^2} = \frac{1}{|h_{i,j}^\text{SR}|^2} + \frac{1}{|h_{i,j}^\text{ST}|^2}$$

where $\eta_{i,j}$ denotes a parameter related to the $i,j$th antenna pair. Since $\eta$ is only related to the channel parameters of the two branches in the ratio, by selecting a ratio with the minimum value of $\eta$ among all the ratios, a lower BER can be obtained.

With $Q$ Reader antennas, $Q(Q-1)/2$ ratio pairs can be formed. It should be noted that for each ratio pair, swapping the numerator and denominator does not affect the value of $\eta$. Thus we further restrict to $i < j$, and only $Q(Q-1)/2$ ratios need to be searched. Subsequently, our antenna selection scheme can be described as follows. First, we compute the value of $\eta$ according to (18) and (25) among $Q(Q-1)/2$ ratios. Next, we select the ratio $\lambda_{\text{opt}}$ which has the minimum value of $\eta$. The detailed optimal ratio selection scheme is shown in Algorithm 1. It can be seen that since $Q(Q-1)/2$ ratios have been exhaustively searched, Algorithm 1 can find the global optimal of $P_t$.

VI. SIMULATION RESULTS

In this Section we provide simulation results to demonstrate the performance of our ratio detector. We first investigate the effect of CSI estimation on BER to determine an appropriate training length. We then provide comparisons with the original ratio detector and the averaging-based energy detector to show the enhanced BER and data rate performance of our ratio detector even with estimated CSI. In the simulation results presented, we assume that all the small-scale channel fading coefficients $h_q^\text{SR}$, $h_q^\text{ST}$ and $h_s^\text{ST}$ follow a $\mathcal{CN}(0,1)$ distribution and the ambient signal follows a CSCG distribution with average power $P_s$. However a result is also provided when $M$-PSK modulated ambient RF signals are utilized to demonstrate the validity of this assumption and the accuracy of the corresponding BER analysis. The hardware implementation loss by the Tag, $\alpha$, is set as 1.1 dB [11] and the relative SNR $\Delta\gamma = -40$ dB [37]. The Monte Carlo method is used to find the BER. Discussions comparing a conventional LR detector with our ratio detector are provided in the Appendix.

A. Channel Estimation

In Fig. 2 we show the BER performance of our proposed ratio detector with perfect and estimated CSI with different $N$ to validate the effectiveness of our proposed CSI estimation method. The ratio detector uses repetition codes and interleaving to enhance its performance where $K = 100, 500, 1000$ and the training sequence length is set as $N = 1000, 5000$. It should be noted that since the backscattered signals are very weak ($\Delta\gamma = -40$ dB), it is essential to use appropriate pilot training lengths to obtain enough samples for averaging to
enhance the estimation accuracy. From Fig. 2, two observations can be made.

First, it can be seen that our channel estimation method has good performance compared with perfect CSI. When BER is $10^{-2}$, the SNR gap between perfect CSI and estimated CSI is 1.6 dB with $K = 500$ and 2.4 dB with $K = 1000$, which shows the accuracy and efficiency of our proposed channel estimation method.

Second, when $K$ is fixed, comparing the two BER curves using perfect and estimated CSI, it can be seen that the performance gap decreases with increases in $\gamma_d$, since higher SNR brings less estimation error. Besides, it can be seen that when $K$ is fixed, decreasing $N$ degrades the BER performance. However, the performance gap is not large. For example, when BER is $10^{-2}$, the SNR gap between $N = 1000$ and $N = 5000$ is about 0.7 dB with $K = 500$ and 1 dB with $K = 1000$, and the gap decreases with increasing SNR. We therefore select $N = 1000$ as a good tradeoff between estimation overhead without significant performance loss. Training with $N = 1000$ is also good in terms of its relative occupied transmission length. For example if the channel coherence time is 500 $\mu$s and the bandwidth is 40 MHz then the proportion of training in the transmission block is 10% when $N = 1000$. Furthermore, pilots’ transmission with $N = 1000$ has reasonably low complexity at both the Tag and Reader side. As we discussed in Section III-E, at the Tag side, transmitting a training sequence of “0” and “1” respectively represents the Tag being silent and then backscattering. Since our system is backscattering, the training process does not require additional power for transmission since the “0” and “1” can be held continuously to create the required repetition. At the Reader side, only averaging and subtraction need to be performed, which is also straightforward and has low complexity. In the remainder of this paper we use $N = 1000$ for all simulations of our ratio detector since it has low estimation overhead, low training complexity, and good BER performance.\(^2\)

\(^2\)It has been demonstrated that with the same symbol rate, the BER performance of coherent detection with pilot training outperforms noncoherent differential detection when it uses the pilot training resources to increase the length of the repetition codeword.

In Fig. 3, we explore BER performance of the estimated CSI under different relative SNR $\Delta \gamma$. The training sequence length is $N = 1000$ and the repetition codeword length is $K = 500$. From Fig. 3, it can be seen that larger $\Delta \gamma$ provides better performance since it indicates that the backscatter signal strength is larger. Besides, with fixed direct link SNR, it can be seen that the performance gap between perfect and estimated CSI decreases with increases in $\Delta \gamma$. When $\gamma_d = 15$ dB, the performance gap for $\Delta \gamma = -40$ dB is 3.3 dB, while for $\Delta \gamma = -35$ dB and $\Delta \gamma = -30$ dB it is about 2.3 dB and 1.8 dB. The smaller performance gap arises from the stronger backscatter signal.

B. Comparison With the Original Ratio Detector With and Without Coding and Interleaving

We first compare the detection performance of the original ratio detector [31] and our proposed ratio detector without coding and interleaving. The simulated BERs versus direct link SNR of the two detectors are shown in Fig. 4. For our proposed ratio detector without coding we have provided four cases, which include the ratio detector using ML (9) with perfect CSI and knowledge of direct link SNR, BER expression (38) with perfect CSI, minimum distance detector (27) with perfect CSI and finally the minimum distance detector with estimated $(N = 1000)$ CSI. Comparing the performance of the original
ratio detector and our proposed detector, four observations can be made.

First, for our proposed ratio detector without coding and interleaving, it can be observed that the optimal ML detector (9) based on the original channel (5) and the minimum distance detector (27) based on the linearized channel (22) have almost the same BERs for both low and high SNR regions. This shows that the proposed linearized channel model (22) approximates the channel (5) over the whole SNR region well. In addition, the BER performance of the proposed ratio detector matches well with the theoretical analysis result (38), which validates the correctness of our BER analysis.

Second, it can be seen that with $N = 1000$ training sequence length, the minimum distance detector using estimated CSI performs only slightly worse than when it has perfect CSI, which again shows the effectiveness and accuracy of our proposed channel estimation method.

Third, comparing the BERs of the original ratio detector with perfect CSI and our proposed detector with estimated CSI, both without coding and interleaving, we can find that at the same SNR point, even when there is CSI estimation error, the proposed ratio detector still has a lower BER. This is because preserving phase information gives the detector more information.

Fourth, it can be seen that for both detectors, the BER curves decrease significantly when the SNR is higher than 25 dB. This is because in Fig. 4, the data rate for the ratio detector is as high as the rate of the ambient signals, so that the average power of the backscattered signal is low at each Tag (or ambient) symbol period, which results in a low receive SNR. Only when the direct link SNR is high enough, it can be ensured that the receive SNR is as high as the level that can detect the bit error. Thus, it is not practical to make the backscatter data rate as high as the ambient data rate. To handle the extremely weak backscattered signals, letting the symbol duration of the backscatter signal be much larger than that of the ambient RF signal is an essential precondition. This can be achieved by repetition codes which allow the backscatter signal to be recovered from the mixed received signals more easily. Besides, as we discussed before, introducing interleaving can further enhance the system performance since channel diversity can also be utilized.

Utilizing our accurate approximate linear channel model (22), we can also include coding and interleaving into our proposed ratio detector as also shown in Fig. 4. This cannot be easily performed for the original ratio detector because of its nonlinear formulation and this is one of the advantages of utilizing our linear channel approximation. In the simulations with coding and interleaving, the symbol duration is $K = 500$, which is 500 times longer than the ambient signal period. It can be seen that after using the repetition code and interleaving, the detection performance of the proposed ratio detector has been greatly improved no matter the CSI is perfectly estimated or not. This is because the interleaving scheme can effectively combat the deep fading phenomenon, and the repetition code can utilize time diversity to lower BER. It can be observed that the BER curve drops sharply and can achieve BER at $10^{-3}$ level around 25 dB, which shows the efficiency of the encoding and detection method proposed in Section IV.

It is also worth noting that for our proposed ratio detector which leverages the linear channel model, the ML detector is simplified to be the minimum distance detector, which greatly reduces the detection complexity. This formulation also provides a closed-form BER expression. Furthermore, benefiting from the channel linearization, coding and interleaving schemes can be easily utilized in the formulation.

C. Comparison With Averaging-Based Energy Detector

In this subsection, the performance of our proposed ratio detector and that of state-of-the-art averaging-based energy detector [37] is compared. The averaging period of the averaging-based energy detector is taken as $K = 100, 500, 1000$ and similarly we also use the same values for coding in our proposed ratio detector to keep the comparisons fair. For simplicity, in the following figures’ legend, “ratio” refers to the proposed ratio detector and “energy” refers to the averaging-based energy detector.

Fig. 5 shows the BER performance of our proposed ratio detector and the energy detector [37], and we have the following observations.

First, for both kinds of detectors, the BERs decrease with increases in $K$ when the direct link SNR is fixed. However, the ratio detector is more responsive to changes in $K$. When $K$ is fixed, the BER for averaging-based energy detection will not decrease when the direct link SNR is large, in other words, there is an error floor. But for the proposed ratio detector, the error floor disappears; on the contrary, the slope of the BER curve increases as the direct link SNR increases.

Second, comparing the performance of the averaging-based energy detector and ratio detector having the same $K$, we can find that with perfect CSI, our proposed detector always outperforms the averaging-based energy detector and the performance gap is impressive. It can be seen that when $\gamma_d = 20$ dB and $K = 1000$, the BER of the proposed detector is almost 40 times lower than the energy detector. Besides, the performance gap increases with increasing direct link SNR, which shows the superiority of our proposed ratio detector and scheme developed in Section IV.
Third, it can be observed that even if the ratio detector uses the estimated CSI, compared with the energy detector with the same $K$ and perfect CSI, when $\gamma_d > 15$ dB, the ratio detector still has better performance, which further validates the superiority of our proposed ratio detector. Besides, the performance gap between the ratio detector having perfect CSI and estimated CSI could be reduced by increasing the length of the training symbols, as shown in Fig. 2. In the following figures, we only show the performance of the ratio detector with estimated CSI.

One of the most important advantages of the ratio detector is the increased data rate. Therefore, in Fig. 6, we compare the BER versus $K$ of the averaging-based energy detector [37] and our proposed detector with repetition code and interleaving. For both of the detectors, the single-antenna Tag and dual-antenna Reader is utilized. We take three different direct link SNRs: 15, 20, 25 dB, and the following two observations can be made from Fig. 6.

First, when $K$ is fixed, both of the detectors achieve lower BER when SNR is increased. However, the proposed ratio detector is more responsive to change in direct link SNR. It can be observed that for the ratio detector, the performance gap between each curve having a different SNR is much larger than that of the averaging-based energy detection.

Second, for both the detectors, increasing $K$ can improve system performance when the direct link SNR is fixed. Nevertheless, with the same direct link SNR, the proposed ratio detector has a lower BER compared with the averaging-based energy detector and the performance gap becomes larger with increases in $K$.

D. Ratio Selection Scheme

To provide quantification of the gains that can be achieved with more than two antennas at the Reader, the BER performance of a 4-antenna ($Q = 4$) Reader utilizing ratio selection is shown in Fig. 7. All results are for estimated CSI. The BER curve of a $Q = 2$ antenna system is shown as a reference. From Fig. 7 it can be seen that by implementing multiple antennas on the Reader, the ratio that has minimum $\eta$ can be selected and the BER is lowered compared with BER of the $Q = 2$ Reader, which validates the effectiveness of our proposed ratio selection scheme. Besides, it can be observed the performance gap increases with the increase of the direct link SNR.

E. Ambient RF Source Comparison

The final result we provide is the exploration of the ambient RF source. In Fig. 8, we compare the BER performance under two different ambient RF sources, $M$-PSK modulated and CSCG distributed ambient RF signals, to evaluate the effectiveness of our proposed linear channel. For $M$-PSK modulated ambient RF signals, we make use of the linear detector (29) to perform detection, and the BER expression (39) to generate the theoretical BER curve. The repetition codeword length $K = 500$. From Fig. 8, two key observations can be highlighted.

First, comparing the performance of the two different RF sources, it can be seen that the BER is lower when ambient RF signals are $M$-PSK modulated with both estimated and perfect CSI. This is because the modulated RF signals are less random.

Second, it can also be seen that comparing the theoretical BER curve and the simulated curve with perfect CSI of $M$-PSK modulated ambient RF signals, the performance gap is small, which shows the correctness of our analysis and verifies the accuracy of our proposed channel model.
We can conclude that our proposed channel model: i) is accurate for both CSCG distributed and M-PSK modulated ambient RF signals; ii) provides a straightforward and low computational complexity detection method for backscattered signals, which is suitable for both kinds of ambient RF signals; and iii) provides closed-form expressions for both kinds of ambient RF signals.

VII. Conclusion and Future Work

In this paper, we have proposed an AmBC system with an efficient ratio detector to overcome the drawbacks of conventional averaging-based energy detectors. Unlike original ratio detectors that use the magnitude ratio of the signals between two Reader antennas, we have utilized the complex ratio so that phase information can be preserved. More importantly, this allows us to devise an accurate linear model for the ratio detector, which can be utilized to open up the use of more standard detection techniques in AmBC systems. Based on the constructed linear channel model, we have proposed the minimum distance detector and derived closed-form expressions of the BER under both CSCG distributed and M-PSK modulated ambient RF signals. With the linear channel model, an efficient and straightforward CSI estimation method has also been proposed. Coding and interleaving can also be straightforwardly applied. Besides, the results are general, allowing any number of Reader antennas to be utilized using our proposed ratio selection scheme. Simulation results demonstrate that the proposed detector is better than averaging-based energy detectors and the original ratio detectors and validate the effectiveness of the channel estimation method. These results indicate that the proposed technique is potentially useful for future AmBC systems.

For future work, it would be valuable to explore the Reader with $Q > 2$ antennas, as there are a variety of ratios to consider and several techniques to utilize them. As a result, determining the optimal method for forming the ratios and the optimal ratio combining technique can be seen as an open problem. Further investigation into this matter would be a useful area of follow-up work. Besides, the extension of our proposed ratio detector to the system consisting of multiple ambient RF sources, multiple passive Tags, and multiple Readers is also worthwhile to explore. For AmBC systems with multiple RF sources from different frequency bands, we can separate different received signals using a band-pass filter. If the multiple RF sources are within the same band then they will add together and help form the CSCG source distribution assumed in AmBC. For the AmBC system with multiple Tags, the time division multiple access (TDMA) method can be used, which has been widely studied in [48], [49], [50], and [51]. The Tag selection scheme can also be adopted [52], [53], [54], [55]. For the AmBC system with multiple Readers, we can also use the TDMA scheme due to its straightforward design.

Appendix

Comparison with LR Detector

In this Appendix we compare the minimum distance detector based on the linear channel model with the coherent LR detector proposed in [15], [24], and [32] that provides optimal detection performance. The decision rule for LR is given by

$$f(\bar{z} | x = 1) \frac{x=1}{x=-1} \frac{1}{1},$$

where $\bar{z} = (\bar{z}_1(n), \bar{z}_2(n))^\top$. It can be seen that if the CSI and the distribution of the ambient RF source are perfectly known by the Reader, the LR detector (48) can achieve optimal performance. However, the LR detector has three limitations: first, the computational complexity for LR detector is high since a complicated detection threshold and multiple eigenvalues need to be utilized in order to decode one backscatter symbol [15], [24], and [32]. This is not straightforward and can result in decoding latency; second, it can be observed that the LR detector’s performance relies on the knowledge of the ambient RF source. If the ambient source is unknown, the LR detector is difficult to implement. However, it is nearly impossible for the Reader to have access to the constellation set of the ambient RF source or know its distribution. Thus, the LR detector is not practical; third, without a linear channel model, it is difficult for the LR detector to perform channel estimation and be combined with other commonly-used linear techniques such as coding and interleaving to further enhance its performance.

In contrast, it is shown that for our ratio detector with the proposed linear channel model, the optimal ML detector reduces to the same straightforward minimum distance detector no matter whether the ambient RF signal is CSCG distributed or M-PSK modulated. This is a significant advantage since the distribution or the constellation set of ambient RF signals is difficult to access and the minimum-distance detector has much lower computational complexity. Besides, with the linear channel model, performing channel estimation is straightforward and conventional linear techniques can be further utilized to improve the BER performance. Thus, although the LR detector can achieve better performance compared with the ratio detector, our proposed ratio detector lowers detection complexity and makes it suitable for AmBC.

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