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Coherent Multi-antenna Receiver for BPSK-modulated Ambient Backscatter Tags

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Abstract—Ambient backscatter communication (AmBC) is an emerging communication technology enabling green Internet of Things deployments. The widespread acceptance of this paradigm is limited by the low signal-to-interference-plus-noise ratio (SINR) of the signal impinging on the receiver antenna due to the strong direct path interference and unknown ambient signal. The adverse impact of these two factors can be mitigated by using noncoherent multiantenna receivers, which are known to require a higher SINR to reach the bit-error-rate (BER) performance of coherent receivers. However, considering the unknown ambient signal, unknown location of AmBC tags, and varying channel conditions, coherent receivers for AmBC systems are rarely studied in the literature. In this article, a coherent multiantenna receiver, which requires no prior information of the ambient signal for decoding the binary-phase-shift-keying (BPSK) modulated signal, is presented. The performance of the proposed receiver is compared with an ideal coherent receiver that has perfect phase information, and also with the performance of a noncoherent receiver, which assumes distributions for ambient signal and phase offset caused by the excess length of the backscatter path. Comparative simulation results show the designed receiver can achieve the same BER performance of the ideal coherent receiver with 1-dB more SINR, which corresponds to 5-dB or more gain with respect to noncoherent reception of on-off-keying modulated signals. Variation in the detection performance with the tag location shows that the coverage area is in the close vicinity of the transmitter and a larger region around the receiver, which is consistent with the theoretical results.

Index Terms—Ambient backscatter, coherent detection, machine learning (ML), noncoherent detection, performance analysis.

I. INTRODUCTION

Recent advances in computing and communication technologies have enabled data exchanges among different devices without human intervention, known as the Internet of Things (IoT). Widespread deployments of IoT networks are inevitably limited by the scarcity of the communication spectrum and the power consumption of the devices. The recently emerging ambient backscatter communication (AmBC) paradigm efficiently handles both limitations while traditional communication technologies fall short for massive IoT deployments [1], [2]. Since the AmBC technology requires neither power-hungry amplifiers nor a dedicated illuminator that generates a specific carrier signal for the sensors, it realizes ultralow power wireless communication [3]. Meanwhile, significant bandwidth efficiency enhancement can be obtained by using the spectrum allocated for a legacy system [4]. Possessing these features, AmBC is becoming a promising component for realizing a sustainable IoT ecosystem.

In a typical AmBC system, a passive backscatter device (BD), often referred to as the tag, operates using the harvested ambient energy [5]. It transmits its information by modulating directly on top of the ambient radio-frequency (RF) signal, such as the cellular network [6], WiFi [7], and digital video broadcasting-terrestrial (DVB-T) [8]. The state-of-the-art tags perform the on-off-keying (OOK) modulation by either backscattering or absorbing the ambient RF signal. The altered signal impinges on the receiver antenna together with the ambient RF signal. Then, the receiver recovers the transmitted tag information from the composite signal. This is usually done by noncoherent detection as it does not require phase synchronization [9]. Detecting the backscatter information at the receiver, however, is limited by two properties of the AmBC system. First, the backscatter signal suffers from strong direct path interference (DPI) [3]. This results from the keyhole channel property of the backscatter path, which causes a substantial signal strength loss. Second, due to the lack of cooperation between the legacy system and the backscatter system, the receiver has little information about the ambient RF signal. These two properties of the backscatter signal particularly hamper its signal-to-interference-plus-noise ratio (SINR), which limits the bit-error-rate (BER) performance of AmBC systems.

The available solutions for addressing the strong DPI and unknown ambient signal are either eliminating the legacy signal using complex signal processing techniques [10], or mitigating their impact using any of the direction [11] or spectral [12] differences between two signals. Among these solutions, direction difference is realized by multiantenna receivers, which address these problems without any information on the ambient signal or on the channels, and they do not put any specific requirements on AmBC system setups. Since a multiantenna receiver provides a higher degree-of-freedom for the implementation compared with other techniques, it is an ideal candidate for improving the observed SINR.

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Another technique to improve the detection performance of the receivers is to use binary-phase-shift-keying (BPSK) modulation at the tag. Compared to the commonly adopted OOK demodulators, BPSK demodulators can achieve the same BER performance with 6-dB less SNR [13, Ch. 4]. In order to achieve all the SNR gain, a BPSK demodulator should be implemented as a coherent receiver. Such a coherent receiver for AmBC systems requires a complex phase synchronization method since the phase of the ambient signal and the channels, and the phase offset caused by the excess length of the backscatter path compared with the direct path are not known at the receiver. Although coherent receivers should take into account all of these phases, multiantenna receivers can be exploited to avoid the first two phases leaving only the last one to be estimated for realizing a coherent BPSK demodulator [11]. However, the low SINR of the tag signal degrades the performance of standard phases estimation techniques and, thus, more complex estimation methods should be adopted. Therefore, the BER performance of AmBC systems, which can be translated to the communication range or achievable rate, is improved by using BPSK modulation at the BD and coherent demodulation at the multiantenna receiver—a solution that has not been investigated in the AmBC literature.

In this article, we introduce a complete AmBC architecture for realizing the coherent reception of the BPSK-modulated tag signal using a multiantenna receiver. We show that a three-state tag, which has an absorbing state and two states for BPSK, is needed for mitigating the DPI and for synchronizing the phase. Thereafter, we design a multiantenna receiver architecture for retrieving the AmBC signal. The receiver uses two beamformers to mitigate the DPI and unknown ambient signal and utilizes a basic classification algorithm, logistic regression (LR), for demodulating the tag signal. The LR algorithm learns the phase offset pattern from a training sequence and predicts the remaining transmitted bits based on the learned pattern. The primary contributions of this article are as follows.

1) We formulate and solve the problem of coherent reception of the BPSK-modulated tag signal at a multiantenna receiver. The designed coherent receiver architecture is equivalent to the optimum coherent receiver, which does not require any prior information on the ambient signal or on the channels and uses a simple classification algorithm to handle the challenging phase offset caused by the excess backscatter path length.

2) We derive the closed-form error probability of a coherent receiver with ideal knowledge of the phase offset to compare its BER performance with the designed receiver performance. The results suggest that the designed receiver achieves the same BER performance as the ideal coherent receiver when the signal has a maximum of 1-dB more SINR, which corresponds to 5 dB or more gain with respect to noncoherent reception of the OOK-modulated tag signal.

3) We also derive the closed-form error probability of a noncoherent receiver for given distributions of the ambient signal and the phase offset. This receiver takes an energy-detector form, and it only works with the OOK-modulated tag signal after canceling the DPI.

4) The developments of this work suggest that there are two key parameters affecting the BER performance of AmBC receivers: a) the SNR of the legacy system and b) the location of the tag. The latter parameter also dictates the coverage of an AmBC deployment and is used for visualizing a spatial variation in the symbol error rate (SER). The results indicate that acceptable performance is achieved when the SNR of the legacy system is high and/or when the tag is in a close vicinity of the transmitter or in a large region (∼20 wavelengths) around the receiver excluding the null beam of the receiver antenna array.

The remainder of this article is organized as follows. In Section II, related studies are reviewed and the notations used throughout this article are introduced. The system model is outlined in Section III. In Section IV, the designed receiver architecture is presented. Theoretical error probabilities for the noncoherent receiver and the coherent receiver with the known phase offset are derived in Section V. In Section VI, the simulation results are presented and important findings are discussed. Finally, the conclusion is drawn in Section VII.

II. BACKGROUND

A. Related Work

Our aim is to design a coherent receiver that achieves the SNR gain of the BPSK-modulated tag signal in AmBC systems. We first discuss relevant works about the increasing communication range in the backscatter system. Next, we provide a literature review of the available solutions for mitigating the strong DPI and the unknown ambient signal. Then, we review the existing phase synchronization methods for coherent receivers. Finally, we study other related techniques for improving AmBC performance.

For traditional bistatic backscatter systems, receivers have been widely studied to increase the communication range [14]–[17]. Backscatter systems use the continuous unmodulated sinusoidal wave as the source signal, which can be easily known by the receivers. The noncoherent receiver [16] and the coherent receiver [17] are designed for the OOK-modulated and frequency-shift keying (FSK)-modulated tag signal, respectively. However, these detectors cannot be applied directly to the AmBC systems as an AmBC system uses the unknown modulated signal of a legacy system as its source signal. The rapidly varying and unknown ambient signal induces a similar effect as the fast fading to the tag signal and causes the backscatter signal to have a low SINR. Therefore, it is one major factor that hampers detection performance.

As discussed in [3] and [18], the backscatter path can be 30 dB weaker than that of the direct path when the tag is 3 m away from the Rx. Several DPI cancelation methods exist for different deployment scenarios. The DPI is mitigated using successive interference cancelation (SIC) by jointly decoding the ambient and backscatter signals when the channel coefficients are available at the receiver [10]. When applying the frequency-shift technique, the tag may shift the frequency of the ambient signal to a higher band [19] or to the guard
bands between orthogonal frequency-division multiplexing (OFDM) symbols [12] so that the DPI can be eliminated by filtering or they may operate on the cyclic prefix bands of OFDM systems [20]. Another way of mitigating the DPI is to utilize multiple antennas at the receiver. The works [11] and [21] have exploited the spatial diversity in order to separate the backscatter path and the direct path from each other, which exempts the AmBC receiver from working with a special ambient signal or from knowing the channel state information. Different from [11] and [21], which are built upon noncoherent receivers, in this work, we present a multiantenna receiver to coherently decode the BPSK-modulated tag signal.

The unknown ambient signal can be eliminated by jointly estimating it along with the tag signal when the channels are known [10]. Such an estimation requires additional information from the legacy system, and thus has limited generality. AmBC receivers may avoid the necessity of tracking the unknown ambient signal by implementing a noncoherent receiver [1], [6], [10], [12], [20]–[26]. These works realize the noncoherent receiver as the maximum likelihood receiver by considering either the OOK modulation or the differential coding at the tag, and provide the theoretical performance analyses of the proposed receivers. For example, the work [23] studies the maximum likelihood receiver and obtains the optimal decision threshold that minimizes the BER performance, the work [24] further investigates the performance of the noncoherent receiver. BPSK modulation is also used with noncoherent receivers, however, it has been reported that a severe error floor problem occurs if the DPI is not canceled [27]. When the DPI is canceled, a BPSK-modulated tag signal cannot be decoded at the noncoherent receiver. Different from these works, in this article, we use a two-stage beamforming to mitigate the impact of the unknown ambient signal on the receiver performance.

Designing a coherent receiver requires a complex phase synchronization because of an unknown phase offset caused by the propagation of the tag signal and unknown channel states. In work [19], two receivers are proposed for AmBC systems when the tag shifts the frequency of the ambient signal to a much higher band. A coherent receiver is derived for constant envelope ambient signal and pseudo-FSK-modulated tag signal; and a partial coherent receiver is presented for a general ambient signal and a hybrid BPSK-FSK modulated tag signal. For both of the receivers, the random phase of the received signal, which is mainly induced by the tag operation, is estimated using the measurements acquired when the tag transmits a short training sequence. The phase offset is visualized in work [28] and several calibration techniques are proposed using preambles of the legacy system. It requires additional information from the legacy system, and thus has limited practical use. Although work [29] proposes a blind channel estimation using the expectation–maximization (EM) algorithm, the method needs prior information about the ambient signal constellation. In this article, we propose a machine learning (ML)-assisted phase synchronization which neither requires a cooperation between the legacy and the AmBC systems nor any prior knowledge of the ambient signal.

Our work is related to several works on demodulation of AmBC systems by predicting the transmitted signal after learning the received signal patterns from training sequences [7], [22]. The work [22] applies an EM-assisted method to retrieve the OOK-modulated tag signal, and [7] extracts a unique slope feature of the received WiFi signal. Nevertheless, these methods require the receiver to know the constellation of the legacy system. Our method does not depend on any information of the legacy system and, thus, is more general than the aforementioned works.

The channel coding technique is essential for improving the successful tag signal recovery rate or the transmission range in backscatter systems as it increases the SNR of the desired signal. The repetition code is commonly performed in prior studies to improve the BER performance. A simple periodic encoding scheme, which avoids the need for synchronization, is proposed in [6]. However, these coding schemes require more redundant bits due to their poor error-correcting performance. Error-correction coding techniques also have been utilized. High-rate and low-complexity channel coding is used considering the limit energy of the tag while the interleaving technique is applied to further tackle the deep fade channel condition [14], [15], [17]. Moreover, special waveform designs have been investigated for the OFDM ambient signal in works [12], [20], [30] to enhance the communication performance of battery-free tags. In this work, we study the impact of well-known coding methods on the receiver performance.

One potential solution to increase the reliability and/or communication range of the AmBC system is adopting multiple antennas at the tag as multiple antennas can mitigate the deep fading of the tag signal [31], [32]. The multiple antennas at the tag can be separated into groups, one of which constantly harvests the energy to support the tag operations, and the optimal antenna is selected to maximize the detection probability of the tag signal [32]. However, a more complicated receiver would be needed to handle the self-interference among the streams when multiple antennas at the tag transmit simultaneously. Therefore, in this work, we focus on the tag with a single antenna configuration and leave the multiantenna configuration as a possible extension to further improve the receiver performance.

Finally, this article is an extension of our previous work [18], which presents an ML-assisted receiver and evaluates its BER performance. In this article, we rigorously derive the proposed receiver from the MAP criterion and analyze a coherent receiver with perfect phase information and a noncoherent receiver. Furthermore, we present a three-state AmBC tag modulator. We carry out frequency-independent simulations to compare the performance of the designed receiver with two receivers. We illustrate the variation in the receiver performance with the tag location to suggest a coverage area for the tag.

### B. Notations

Throughout this article, scalars are denoted by normal italic font letters $a$, and vectors and matrices are represented by lower-case $a$ and upper-case $A$ boldface letters, respectively. Complex valued scalars are assumed, and $\text{Re}[a]$ and $\text{Im}[a]$
denote the real and the imaginary parts of a scalar \( a \), respectively. The Euclidean norm of a vector \( a \) is denoted by \( \| a \| \). The \( n \times n \) identity matrix is \( I_n \), and the subscript \( n \) may be omitted sometimes for notational convenience. The conjugate-transpose, conjugate, and transpose of a matrix \( A \) are \( A^H \), \( A^* \), and \( A^\top \), respectively, and \( \text{rank}(A) \) is its rank. We use \( \mathcal{CN}(m, \Sigma) \) to denote the complex Gaussian variable with mean \( m \) and covariance matrix \( \Sigma \). The statistical expectation is \( E[\cdot] \), variance is \( \text{Var}[\cdot] \), and probability of an event is \( \mathcal{P}[\cdot] \). The imaginary number is \( j = \sqrt{-1} \).

III. PROBLEM FORMULATION

In this article, we consider a basic AmBC system, which consists of a BD (Tag), a separated legacy ambient source (Tx), and an AmBC receiver (Rx) with \( N_r \) antennas as shown in Fig. 1. In the illustrated scenario, the passive tag modulates its own information onto the ambient signal, and the Rx receives both the ambient signal and backscatter signal. In this section, we present a system model for this scenario, define the general terms used throughout this article, and give practical assumptions on the wireless channels, the ambient signal, and the tag signal.

A. Channel Model

In this article, without loss of generality, we consider a 2-D Euclidean space with the Cartesian reference frame shown in Fig. 1. The first receiver antenna out of \( N_r \) elements is selected as the reference antenna. The line connecting the Tx and the reference antenna is set to be the \( x \)-axis and the middle point of this line segment is set as the origin of the reference frame. The position of the \( l \)th Rx antenna, \( l = 1, \ldots, N_r \), the position of the Tx, and the position of the tag are denoted by \( p_l \), \( P \), and \( p_t \), respectively. Then, the distance between the Tx and the \( l \)th Rx antenna is \( d_{0l} = \| p_l - P \| \), the distance between the tag and the \( l \)th Rx antenna is \( d_{1l} = \| p_l - p_t \| \), and the distance between the Tx and the tag is \( d_2 = \| P - p_t \| \).

We consider a quasistatic deployment in which three nodes move slowly enough to keep the channels constant for the duration of a frame. Hence, we assume block fading, where the channel coherence time exceeds the transmission duration of a frame. However, the channel may still vary from one frame to another because of varying multipath components over time. Let the vectors \( \tilde{a} = [\tilde{a}_1, \ldots, \tilde{a}_{N_r}] \) and \( \tilde{h} = [\tilde{h}_1, \ldots, \tilde{h}_{N_r}] \) represent the channel gains of the direct path and the backscatter path seen at the Rx antenna array, respectively. The direct path channel \( \tilde{a} \) is the phasor sum of all the multipath components that are not modulated by the tag, while the backscatter path channel \( \tilde{h} \) is the phasor sum of the multipath components that are modulated by the tag. The average large-scale path loss based on deployment geometry and free space in the presence of line-of-sight (LOS) components can be represented as [33], [34]

\[
\begin{align*}
E\{\|\tilde{a}\|^2\} &= \left(\frac{\lambda}{4\pi d_{0l}}\right)^2 \\
E\{\|\tilde{h}\|^2\} &= \left(\frac{\lambda}{4\pi d_{1l}}\right)^2 \left(\frac{\lambda}{4\pi d_2}\right)^2 
\end{align*}
\]

(1)

where \( \lambda = f_c/c_0 \) is the carrier wavelength, \( f_c \) is the carrier frequency, and \( c_0 \) is the free-space electromagnetic propagation speed. The channel gains of two paths are normalized with respect to the channel gain of the direct path so that

\[
\tilde{a} = \frac{\tilde{a}}{\|\tilde{a}\|}, \quad \tilde{h} = \frac{\tilde{h}}{\|\tilde{a}\|}
\]

B. Tag Signal

As can be seen from (1), the term \( (\lambda/(4\pi))^2 \) results in an extensive power loss for the backscatter path such that its effective SNR is still relatively low even after the DPI cancelation. We use two techniques at the tag in order to improve the effective SNR of the backscatter signal. First, the tag adopts BPSK modulation by altering the antenna impedance to switch the phase of the incident RF signal. Second, we utilize the orthogonal Hadamard code and nonorthogonal Simplex code, which are commonly used due to their easy implementation [35]. The Hadamard code is able to correct many errors by sacrificing the efficiency, which makes it a good candidate for noise-corrupted backscatter channels. The Simplex code achieves the same performance as a Hadamard code with one dimension less codewords [35].

At the tag, a data-bit sequence \( B \) of \( \{0, 1\} \) is segmented into \( P \) length-\((r + 1)\) tuples. The length-\((r + 1)\) tuple is encoded to a length-\(n \) code word \( n = 2^{r+1} \) by using the generator matrix, where \( r \) is called the code order. The Hadamard code generator matrix \( G_{H,r} \) of order \( r \) can be expressed as [36]

\[
G_{H,r} = \begin{bmatrix} G_{H,r-1} & J_{r-1} \oplus G_{H,r-1} \end{bmatrix}, \quad r \geq 2
\]

\[1\] Although the link budget also includes the on-object gain penalties of the tag antenna and the path blockage losses, these terms can be ignored in a carefully designed deployment.
Correspondingly, the generator matrix for the Simplex code where \( S \) is closed and \( 3 \) length-
length transmission line with length \( \lambda / 4 \) that all the signal energy is reflected. Since there is an extra
change the reflection coefficient \([37]\). Specifically, when two
backscattering is achieved by altering the load impedance to
equal to the conjugate of the antenna impedance. In principle,
switches \( S_1 \) and \( S_2 \) are both open, it matches the
absorbed state, i.e., \( x = 0 \).

where \( G_{H,r} \) is an \((r+1) \times 2^{r+1}\) matrix, \( J_{r-1} \) and \( G_{H,r-1} \) have
the same size, \( \oplus \) is the binary addition operator, and

\[
G_{H,1} = \begin{bmatrix}
1 & 0 & 0 & 1 \\
0 & 1 & 0 & 1
\end{bmatrix}, \quad J_r = \begin{bmatrix}
1 & 1 & \cdots & 1 \\
0 & 0 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 0
\end{bmatrix}.
\]

Correspondingly, the generator matrix for the Simplex code
\( G_{S,r} \), a \((r+1) \times (2^{r+1} - 1)\) matrix, can be obtained by removing
the all-zero column from \( G_{H,r} \). Denoting the \( \ell \)th tuple, \( \ell = 1, \ldots, P \), as
\( b_{r,\ell} = [b_0,\ell, b_1,\ell, \ldots, b_r,\ell] \). The resulting
codeword \( \tilde{x}_\ell \), also referred to as symbol, can be obtained from
\( b_{r,\ell} \) as

\[
\tilde{x}_\ell = G(b_{r,\ell} \oplus G_r)
\]

where \( G_r \in \{G_{H,r}, G_{S,r}\} \) and \( G(\cdot) \) is the mapping \( 0 \rightarrow -1, 1 \rightarrow 1 \).

The transmitted frame within one channel coherence time is
shown in Fig. 2(a). The transmitted \( P \) symbols, which are composed of \((-1, 1)\), are denoted as \( X = [\tilde{x}_1, \ldots, \tilde{x}_P] \).
Before transmitting \( X \), three length-
preambles of only 0, only +1 or only −1 are prepended. Hence, a frame of the
AmBC tag signal of length \( N = 3L + nP \) is represented as

\[
[x[1] \cdots x[3L]] \quad \text{where } x[1] = \cdots = x[L] = 0, x[L + 1] = \cdots = x[2L] = +1, \text{ and } x[2L + 1] = \cdots = x[3L] = -1.
\]

The frame design requires a tag modulator that can be
switched to any of three states. An implementation of such
a tag is shown in Fig. 2(b), which consists of two single-pole switches \( S_1 \) and \( S_2 \) and a load with \( Z_L \) impedance that is
equal to the conjugate of the antenna impedance. In principle,
backscattering is achieved by altering the load impedance to
change the reflection coefficient \([37]\). Specifically, when two
switches are open, energy is absorbed by \( Z_L \), and \( x = 0 \). When
either of the switches is closed, the load impedance is 0 such
that all the signal energy is reflected. Since there is an extra
transmission line with length \( \lambda / 4 \), the reflected signals with

respect to two switches have a phase difference of \( \pi / 2 \) radians, which realizes +1 and −1 of the BPSK modulation.

The tag modulates the information bits by only changing the phase of the ambient signal.\(^2\) However, the tag circuit design and practical implementation cause a certain power loss at the
modulator, which could result from the mismatch of the
load impedance and the antenna impedance, the transmission
line characteristic impedance, and the nonzero impedance of
the switch when it is closed \([38]\). Such power loss decreases
the SNR of the backscatter signal seen at the receiver antenna array. Let us define the scattering efficiency of the tag, which
quantifies the power attenuation at the tag modulator as

\[
\rho = \frac{P_{\text{out}}}{P_{\text{in}}}
\]

where \( P_{\text{in}} \) denotes the signal power incident on the tag antenna and \( P_{\text{out}} \) is the signal power scattered from the tag antenna to the Rx.

It is worth mentioning that there is a signal component scattered from the tag which is caused by the load-independent tag antenna structural mode \([38], [39]\). Since the structural mode
only creates an additional multipath component, which is not altered by the tag operation, for the channel between Tx and Rx, it contributes to channel \( \tilde{a} \).

\[\text{C. Received Signal at the Rx}\]

Let us denote the \( i \)th ambient signal transmitted from Tx within one channel coherence time as \( \tilde{s}[i] \sim CN(0, 1), \forall i = 1, \ldots, N \). Let us denote the averaged SNR of the ambient signal received at the Rx as \( \gamma \), which we refer to as the SNR
of legacy system. When the signal reaches the Rx reference antenna, it propagates through the direct path channel \( \tilde{a} \) so that it becomes

\[
\sqrt{\gamma} \tilde{a} \tilde{s}[i] = \sqrt{\gamma} a e^{j\phi_0} \tilde{s}[i]
\]

where \( \phi_0 \) is the phase shift caused by the propagation. The ambient signal traversing along the backscatter path is given by

\[
\sqrt{\gamma} \sqrt{\rho} \tilde{h}[i] x[i] = \sqrt{\gamma} \sqrt{\rho} e^{j(\phi_0 + \phi)} \tilde{h}[i] x[i]
\]

where \( \phi \) is caused by the excess length of the backscatter path\(^3\) and \( x[i] \) is a one-bit sample out of length-
N tag frame. Since we are not interested in \( \tilde{s}[i] \), we use \( s[j] = \tilde{s}[i] e^{j\phi_0} \) to denote the ambient signal for notational convenience.

One realization of the variation in the phase offset as a function of tag location is illustrated in Fig. 3, where the Tx antenna and the Rx reference antenna are marked by red circles. It can be observed that a small change in the tag location causes a large variation in \( \phi \). The phase variation is the highest when the tag is close to either Tx or Rx. Therefore, ignoring the phase offset while decoding the tag information degrades the receiver performance.

\[\text{2} \text{We assume the tag has harvested enough power for switching within different impedance, i.e., } Z_L, S_1, \text{ and } S_2.\]

\[\text{3} \text{As represented in (1), the channels are random among different channel realizations, which indicates the propagation lengths of two channels as well as the phase offset } \phi \text{ are random and changing among different channel coherence time.}\]
The component of $h$ on $e$ is a real number by definition of $e$. 

A. Direct Path Interference Elimination

The received signal $y[i]$ is composed of both ambient signal and tag signal, which can be separated if the directions of these two paths are known, or estimated using the acquired samples. For this purpose, the received signal sample matrix corresponding to the first part of the preamble $Y_0$ is used to estimate the direct path direction $a$.

By computing the eigenvector corresponding to the largest eigenvalue of the sample covariance matrix of $Y_0$, i.e.,

$$\hat{a} = \arg \max_{\|v\|=1} \frac{1}{L} \sum_{i=1}^{L} y[i] Y_0^H v.$$  

For the rest of the frame transmission, we eliminate the DPI by projecting the received signal into the orthogonal space of $\hat{a}$, which yields a residual signal given by

$$r[i] = (I - \hat{a}\hat{a}^H)y[i]$$

$$= \sqrt{\gamma} \sqrt{\rho e^{j\phi}} \eta_2 \hat{s}[x[i]] + \left(I - \hat{a}\hat{a}^H\right)\omega[i]$$  \hspace{1cm} (4) 

for $i = L + 1, \ldots, N$.

B. MAP Receiver

The residual signal given in (4) only contains the tag signal in the direction $c$ (see Fig. 1). This direction can be estimated using the same approach as in the previous section. For this purpose, let us denote $Y_t = (I - \hat{a}\hat{a}^H)Y_t$ as the residual signal matrix over the remaining two preambles. Then, the estimate of direction $c$ is given by

$$\hat{c} = \arg \max_{\|v\|=1} \frac{1}{2L} y[i] Y_t^H Y_t v.$$  

Thereafter, the Rx performs the beamforming to combine the residual signal at each antenna, which yields the effective tag signal

$$u[i] = \hat{c}^H r[i] = \hat{c}^H y[i]$$

$$= \sqrt{\gamma} \gamma_t e^{-j\phi} \eta_2 \hat{s}[x[i]] + \hat{c}^H \omega[i]$$  \hspace{1cm} (5) 

where $\gamma_t = \gamma \rho |\eta_2|^2$ is the effective SNR of the backscatter signal and $e^{j\phi} \omega[i] \sim \mathcal{CN}(0, 1)$ is the projected noise. The following proposition gives the test statistics for an optimum receiver.

**Proposition 1:** For the effective backscatter signal in (5), the test statistic of the optimum receiver for the tag signal reads as [40, Ch. 4]

$$R[e^{-j\phi} s^*[x[i]]] = \Re \left[ e^{-j\phi} s^* y[i] \right]$$

$$= \Re \left[ e^{-j\phi} s^* y[i] \right]$$

$$= \Re \left[ e^{-j\phi} \hat{y}[x[i]] \right]$$

$$= \cos \phi \cdot \Re \left[ s[i] \right] + \sin \phi \cdot \Im \left[ s[i] \right]$$  \hspace{1cm} (6) 

where $\hat{s}[x[i]] = \hat{a}^H y[i]$ and $v[i] = \hat{s}^*[x[i]] u[i]$.

**Proof:** See Appendix A.

The above result indicates that the test statistic of the optimum receiver is $R[e^{-j\phi} s^*[x[i]]]$, which is a correlation receiver [40, Sec. 4.4]. Its performance is affected by the unknown random phase offset $\phi$ which brings a rotation to
the decisions are made by comparing the real part of the rotated $v[i]$ with 0, i.e., the decision boundary is the imaginary axis. As shown in Fig. 5(a), after phase rotation, the arrow becomes the real axis and the decision boundary becomes the imaginary axis. However, in practice, it is challenging to compensate for $\phi$ as the performance of well-known phase estimation methods for low SINR effective signal $u[i]$ are not acceptable. Ignoring $\phi$ but only looking at $\text{Re}[v[i]]$ downgrades the BER performance as shown in Section VI. An extreme case is when $\phi = \pi/2$ radians ($\text{Re}[v[i]] = 0$), which yields the test statistic to be $\text{Im}[v[i]]$, although the tag signal may still be decoded. Therefore, for coherent AmBC receivers, $\phi$ must be compensated for by other means.

As can be seen in Fig. 5(a), the instantiated $v[i]$ fall into two clusters, which implies that a linear ML classification algorithm can be used for classifying two clusters. This process implicitly tackles the impact of unknown $\phi$ by learning its pattern from $v[i]$. It is equivalent to rotating the complex plane to separate $v[i]$ and, hence, it is equivalent to the optimum correlation receiver. In the next section, we elaborate on ML classification algorithms which use $\text{Re}[v[i]]$ and $\text{Im}[v[i]]$ as their features.

### C. ML-Based Demodulation

The data set $[\text{Re}[v[i]], \text{Im}[v[i]]]$ instantiated in Fig. 5(a) shows that there exist outliers, and the data set corresponding to $x = +1$ and $x = -1$ classes are overlapping because of the low SINR of the tag signal. As SINR increases, the overlapping area diminishes. However, it will not disappear according to the data distribution, which we will analyze in the next section. Therefore, both linear and nonlinear classifiers can be utilized for the purpose.

The well-known linear classifiers, including the logistic regression (LR), soft margin support vector machine (SVM), linear discriminant analysis (LDA), least-square-based classifier, and a simple nonlinear classifier, $k$-nearest neighbor (kNN), are candidates for learning the pattern from the data set. Among these algorithms, the soft margin SVM can be configured by using a hyperparameter $C$ to control the weight of soft margin latent variables, which, in turn, defines how well it fits to the training data. Although SVM and LR have similar cost functions, LR casts the fitting problem using the Sigmoid function and looks at the probabilities of an observation being in either of the classes. The SVM has similar performance to LR when $C$ is adjusted. The least-squares-based classifier obtains the parameters by minimizing the prediction error, and LDA obtains the parameters by maximizing the class separation. However, for predicting the BPSK-modulated tag signal with equal probability, they are equivalent to each other.

$v[i]$. In order to elucidate the receiver, in Fig. 5(a), we visualize an example sequence of $v[i]$ in the complex plane when $x = +1$ and $x = -1$ within one channel coherence time.$^5$

For normal correlation receivers, the phase offset $\phi$ is estimated and compensated for. In this case, $v[i]$ are rotated and

$^5$Note that positions of the clusters vary with the channel conditions and the SNR of legacy system. The effective signal values shown in Fig. 5(a) are acquired within one channel coherence time.
other [41, Ch. 4]. The nonlinear kNN classifies data intuitively by assigning it to the class which has the majority votes among $k$ selected nearest neighbors. The selection criterion for a classification method includes its performance but also its computational requirements and the length of the training data must be taken into account.

Let us denote $V_l = Y_l^H \hat{a} c^H Y_l$, as test statistics of two length-$L$ preambles, which are used as the training set to calculate the decision boundary of two classes. The rest of the transmitted bits are classified by comparing their test statistics with the decision boundary. An example of the BER performance of different ML algorithms is shown in Fig. 5(b). It shows that in the low SNR region, these ML algorithms have almost the same performance. In the high SNR region, the soft margin SVM and the LR still have a similar performance, and they outperform the others. As discussed above, the LDA and the least square classification also perform similarly, but compared with the SVM and the LR, they lack the robustness against the outliers. Also, the assumption of the LDA that the observations of each class follow a Gaussian distribution is not applicable to the studied case. On the other hand, the kNN has acceptable performance as has been evaluated in our previous work [18]. It can be highly accurate with a large training size and for a carefully adjusted number of neighbors parameter $k$. However, this requirement cannot be always satisfied since short preambles should be designed in order to save tag energy. Furthermore, a large preamble size and $k$ also introduce a high computational burden and a higher memory requirement. Consequently, the LR classifier is the most suitable for mitigating the impact of the unknown phase offset $\phi$.

D. Decoder

The output of the classifier, $P$ distorted symbols denoted by $\hat{X} = [\hat{x}_1, \ldots, \hat{x}_P]$ are then input into a hard-decision decoder to recover the data bits [13, Sec. 7.5]. In this article, a conceptually simple minimum-distance decoding is adopted since the main focus is on the demodulation. The decoding process for one received symbol is done by comparing it with $n$ possible transmitted codewords and selecting the one that has the lowest Hamming distance. This can be achieved by correlating $\hat{x}_\ell$, $\ell = 1, \ldots, P$ with $n$ codewords and outputting the one with the largest correlation. Finally, after retrieving all the data bits, the BER as well as SER of the AmBC system can be calculated.

V. CONVENTIONAL RECEIVERS

In this section, two conventional receivers are elaborated on. The first one is the coherent receiver which requires knowledge of the phase offset, and the other is the noncoherent receiver which averages out the ambient signal and the phase offset. First, error probabilities of two receivers are given. Then, relative parameters associated with the detection performance are discussed.

A. Coherent Receiver for Known Phase Offset

The coherent receiver requires the knowledge of the phase offset at the Rx. To analyze its error performance, we also assume two directions, i.e., $a$ and $c$ are perfectly known at the receiver. Let us rewrite its test statistic in (6) as

$$\zeta = \text{Re}(e^{-j\phi} y^H ac^H y) = y^H \left(\frac{e^{j\phi} ac^H + e^{j\phi} ca^H}{2}\right) y \triangleq y^H My.$$ 

In what follows, we obtain the distribution of $\zeta$ and investigate the detection threshold as well as error performance of the coherent receiver.

In Appendix B, it is shown that the distribution of $\zeta$ conditioned on $x_m$, $m \in \{0, 1\}$ follows asymmetric Laplace distribution (ALD) [42, Ch. 3] of which the cumulative density function (CDF) and probability density function (PDF) are given by

$$F(\zeta | x_m) = \begin{cases} -\frac{\lambda_1(x_m)}{\lambda_2(x_m) - \lambda_1(x_m)} e^{-\frac{\zeta}{\lambda_1(x_m)}}, & \zeta < 0 \\ 1 - \frac{\lambda_2(x_m)}{\lambda_2(x_m) - \lambda_1(x_m)} e^{-\frac{\zeta}{\lambda_2(x_m)}}, & \zeta \geq 0 \end{cases}$$

(7a)

and

$$f(\zeta | x_m) = \frac{1}{\lambda_2(x_m) - \lambda_1(x_m)} \begin{cases} e^{-\frac{\zeta}{\lambda_1(x_m)}}, & \zeta < 0 \\ e^{-\frac{\zeta}{\lambda_2(x_m)}}, & \zeta \geq 0 \end{cases}$$

(7b)

respectively, where $\lambda_\ell(x_m)$, for $\ell = 1, 2$ are two eigenvalues of $M = R y^H x_m$, and $R y^H x_m$ denotes the covariance matrix of received signal $y$ conditioned on $x_m$.

The conditional PDF of the quadratic form in (7b) indicates that $\zeta$ follows the ALD with the location parameter 0, the scale parameter $\sqrt{-1/(\lambda_1(x_m) \lambda_2(x_m))}$, and the asymmetry parameter $\sqrt{-\lambda_1(x_m)/\lambda_2(x_m)}$. The expectation and variance of this distribution are $E[\zeta | x_m] = -\lambda_2(x_m) - \lambda_1(x_m)$ and $\text{Var}[\zeta | x_m] = \lambda_2^2(x_m) + \lambda_1^2(x_m)$, respectively. Two examples of the PDF of two ALD random variables are illustrated in Fig. 6 for different values of the legacy system SNR $\gamma$ when the tag uses BPSK modulation.

The two eigenvalues of the matrix $M$ can be more easily written in terms of

$$e_m = \text{Re} \left\{ \frac{\gamma}{2} \eta_2 \left( e^{j\phi} \rho \eta_1 |x_m|^2 + \sqrt{\rho x_m^*} \right) \right\}$$

(8a)

In the remaining part of this article, we will drop the time dependence of $y$ since the detection of the tag signal is based on a single sample of $y$. 

Fig. 6. PDFs of $\zeta$ conditioned on the BPSK-modulated tag signal for different SNR of the legacy system $\gamma$. 

---

\[ \text{PDF of two ALD random variables are illustrated in Fig. 6 for different values of the legacy system SNR $\gamma$.} \]
\[ A_m = \frac{\gamma}{4} \left( 1 + \sqrt{\rho e^{i \phi}} \eta_1 x_m + \sqrt{\rho} e^{-i \phi} \eta_1^* x_m^* \right) \\
+ \left( |\eta_1|^2 + |\eta_2|^2 \right) \rho |x_m|^2 + \frac{1}{\gamma} \] (8b)

so that the eigenvalues read as

\[ \lambda_\ell (x_m) = \varepsilon_m + (1)^\ell \sqrt{\varepsilon_m^2 + A_m}, \quad \ell \in \{1, 2\}. \] (9)

Using the quantities in (8), let us investigate the behavior of the eigenvalues under practical values of the physical parameters. For a practical AmBC signal when \( \eta_2 \neq 0 \), \( |\eta_1|^2 + |\eta_2|^2 \ll 1 \) so that \( |x_m| \gg |\eta_1| \), which implies \( \varepsilon_m \approx \text{Re} \{ \frac{1}{2} \sqrt{\rho} \eta_2 x_m^* \} \).

The same line of reasoning leads to \( A_m \approx (\gamma/4) \), which, in turn, implies \( (\varepsilon_m^2 + A_m) \approx A_m \). Then, the eigenvalues can be approximated by

\[ \lambda_\ell (x_m) \approx \text{Re} \left\{ \frac{\sqrt{\gamma}}{2} \sqrt{\rho} \eta_2 x_m^* \right\} + (1)^\ell \sqrt{\frac{\gamma}{2}}. \] (10)

In Appendix B, we show the test statistic \( \zeta \) conditioned on two tag signal \( x_0 \) and \( x_1 \) have opposite expectations, and have similar variances, and enlarging the difference between two expectations improves the demodulation performance. In order to see the conditions on how to further move two expectations apart, it is possible to use the approximation of the eigenvalues in (10). Using this approximation, the expectation can be written as \( E[\zeta | x_m] \equiv -\text{Re} \{ \sqrt{\rho} \eta_2 x_m^* \} \), which implies that the detection performance can be improved by increasing the SNR of the legacy system \( \gamma \) or by having a larger backscatter path component that is perpendicular to the direct path \( \eta_2 \).

The binary tag signal demodulation problem can be cast as a binary hypothesis testing, and the optimal receivers can be constructed starting from the MAP criterion. When the tag transmits \( x_0 \) and \( x_1 \) with equal probability, the MAP criterion is equivalent to the maximum likelihood criterion, which compares the likelihood probabilities of the test statistics for a given tag signal, that is

\[ f(\zeta | x_0) \frac{H_0}{H_1} \geq f(\zeta | x_1). \] (11)

Taking the logarithm of both sides of (11), we have

\[
\begin{cases}
\frac{H_0}{H_1} \geq \frac{\Delta_1 (x_0) \lambda_1 (x_1)}{\lambda_1 (x_0) - \lambda_1 (x_1)} \ln \frac{\lambda_2 (x_0) - \lambda_1 (x_0)}{\lambda_2 (x_1) - \lambda_1 (x_1)}, & \zeta < 0 \\
\frac{H_0}{H_1} \geq \frac{\Delta_2 (x_0) \lambda_2 (x_1)}{\lambda_2 (x_0) - \lambda_2 (x_1)} \ln \frac{\lambda_2 (x_0) - \lambda_1 (x_0)}{\lambda_2 (x_1) - \lambda_1 (x_1)}, & \zeta \geq 0.
\end{cases}
\]

This test yields two thresholds with different signs as

\[ T_1 = \frac{\Delta_1 (x_0) \lambda_1 (x_1)}{\lambda_1 (x_0) - \lambda_1 (x_1)} \ln \frac{\lambda_2 (x_0) - \lambda_1 (x_0)}{\lambda_2 (x_1) - \lambda_1 (x_1)} < 0 \]

\[ T_2 = \frac{\Delta_2 (x_0) \lambda_2 (x_1)}{\lambda_2 (x_0) - \lambda_2 (x_1)} \ln \frac{\lambda_2 (x_0) - \lambda_1 (x_0)}{\lambda_2 (x_1) - \lambda_1 (x_1)} \geq 0. \]

It can be observed that the thresholds depend on the ratio of \( \lambda_1 (x_0) - \lambda_1 (x_1) \) and \( \lambda_2 (x_0) - \lambda_2 (x_1) \). Then, (10) implies that

\[ \lambda_\ell (x_m) - \lambda_\ell (x_1) \approx \frac{\sqrt{\rho} \eta_2 \text{Re} \{x_0^* - x_1^*\}}{2 \sqrt{\rho} \eta_2}, \]

so that the sign of the eigenvalue differences can be judged by looking at the difference \( x_0^* - x_1^* \). For the modulation schemes that we consider in this article,\(^7\) we always have \( x_0 < x_1 \), and the domains of the thresholds imply that the error probability should be calculated under two different cases.

1) \( \lambda_1 (x_0) - \lambda_1 (x_1) \leq \lambda_2 (x_0) - \lambda_2 (x_1) < 0 \)

\[ T_2 < 0 \implies \left( \frac{\zeta}{\tilde{H}_1} \right)_{\tilde{H}_0} \implies p_e = \frac{1}{2} \int_{-\infty}^{T_1} f(\zeta | x_0) d\zeta + \int_{T_1}^{\infty} f(\zeta | x_0) d\zeta. \]

2) \( \lambda_2 (x_0) - \lambda_2 (x_1) < \lambda_1 (x_0) - \lambda_1 (x_1) \leq 0 \)

\[ T_1 \geq 0 \implies \left( \frac{\zeta}{\tilde{H}_1} \right)_{\tilde{H}_0} \implies p_e = \frac{1}{2} \int_{-\infty}^{T_2} f(\zeta | x_0) d\zeta + \int_{T_2}^{\infty} f(\zeta | x_0) d\zeta. \]

Another situation occurs when \( \eta_2 = 0 \), which leads \( \varepsilon_m = 0 \), \( \lambda_\ell (x_m) \approx (1)^\ell (\sqrt{\gamma/2})[1 + \sqrt{\rho} \eta_1 x_m] \). In this case, the probability of error should be calculated using the following.

3) \( \lambda_1 (x_0) - \lambda_1 (x_1) > 0 \)

\[ T_1 < 0 \text{ and } T_2 \geq 0 \implies p_e = \frac{1}{2} \int_{-\infty}^{T_1} f(\zeta | x_0) d\zeta + \int_{T_1}^{T_2} f(\zeta | x_0) d\zeta + \int_{T_2}^{\infty} f(\zeta | x_0) d\zeta. \]

This condition implies that the BD is on the direction \( a \), and the receiver cannot discriminate it from the ambient signal. When the number of receiver antennas \( N_r \) is large, this might only happen when the tag is at the transmitter. As \( N_r \) gets smaller, this condition is observed when the tag is in the close neighborhood of the line connecting the Tx to the Rx.

The decision thresholds \( T_1 \) and \( T_2 \) are functions of the components of backscatter path \( \eta_1 \) and \( \eta_2 \). Thus, the decision threshold varies with tag locations and, in turn, the error probability integral boundaries given above change. The variation in the effective condition as a function of location of the tag is visualized in Fig. 7. Although the first two conditions vary similar to the ellipses shown in Fig. 3, the third condition is only observed when the tag is on the line segment between the Tx and Rx.

In practical implementations, the receiver calculates the decision thresholds \( T_1 \) and \( T_2 \) and four eigenvalues using the preamble measurements \( Y_{i+} \) and \( Y_{i-} \), and the direction estimates \( \hat{a} \) and \( \hat{c} \).

B. Noncoherent Receiver

Another typical method to detect the tag signal is the noncoherent receiver, which requires statistical information on the unknown parameters. The noncoherent receivers marginalize over unknown parameters which, in our case, are the ambient signal \( s \) and the phase offset \( \phi \). Recalling that we have obtained the effective backscatter signal through two-stage beamforming given in (5), the likelihood function of \( u \) given \( x_m \) can be

\(^7\)For BPSK modulation, \( x_0 = -1 \) and \( x_1 = +1 \); for OOK modulation \( x_0 = 0 \) and \( x_1 = +1 \).
written as
\[
\rho(u|x_m) = \pi f(u|x_m, \phi)f(s)f(\phi)d\phi
\]
\[
= \frac{1}{\pi (\gamma \rho|\eta|^2|x_m|^2 + 1)} \exp \left\{ -\frac{|u|^2}{\gamma \rho|\eta|^2|x_m|^2 + 1} \right\}.
\]
Substituting it into the maximum likelihood criterion expressed in (13) and taking the logarithm on both sides yields
\[
|u|^2 \leq H_0
\]
which shows that the test statistic of the noncoherent receiver is $|u|^2$. In other words, the optimum noncoherent receiver is the energy detector when the statistics of $s$ and $\phi$ follows the assumed distributions. The threshold of the test $T_h$ is given by
\[
T_h = \frac{(\gamma_e|x|^2 + 1)(\gamma_e|x|^2 - |x|^2)}{\gamma_e(2|x|^2 - |x|^2)} \ln \left( \frac{\gamma_e|x|^2 + 1}{\gamma_e|x|^2 + 1} \right).
\]
It can be seen that $T_h$ goes to infinity when the tag signal is BPSK-modulated, which implies that the noncoherent receiver is useful only when the tag changes the amplitude of $x$, e.g., by using the OOK. In this case, the measurement is tested for the presence of the tag signal against the absence of it, and the threshold is
\[
T_h = \left( 1 + \frac{1}{\gamma_e} \right) \ln (\gamma_e + 1).
\]
The noncoherent receiver derivations given above can be used for receiver performance analysis for an OOK-modulated tag signal. Under $H_0$, the effective signal is $u = e^{jH}\omega$, and it is easy to see that $2|u|^2$ follows the chi-square distribution with 2 degrees of freedom, i.e., $2|u|^2 \sim \chi^2_2$. Based on this statistic, the probability of false alarm is given by [13, Sec. 2.3]
\[
P_f = \mathbb{P} \left( |u|^2 > T_h | H_0 \right) = 1 - \bar{\Gamma}(1, T_h).
\]

where $\bar{\Gamma}(s, x)$ is the lower incomplete Gamma function
\[
\bar{\Gamma}(s, x) = \int_0^x t^{s-1}e^{-t}dt.
\]
Under $H_1$, (5) is written as $u = \sqrt{\gamma_e} + e^{jH}\omega$, which follows $CN(0, \gamma_e + 1)$. Then, $(2/\gamma_e + 1)|u|^2$ follows the chi-square distribution with 2 degrees of freedom. The probability of miss detection for this statistic is
\[
P_M = \mathbb{P} \left( |u|^2 \leq T_h | H_1 \right) = \Gamma \left( 1, \frac{T_h}{\gamma_e + 1} \right).
\]
Hence, the error probability is given by
\[
p_e = \frac{1}{2} \left[ 1 + \bar{\Gamma} \left( 1, \frac{T_h}{\gamma_e + 1} \right) - \bar{\Gamma} \left( 1, T_h \right) \right]. \tag{12}
\]
For this noncoherent receiver, only the amplitude-modulated backscatter signal can be detected, e.g., OOK-modulated tag signal, after the mitigation of the DPI. The error probability in (12) is defined by the effective SNR of the backscatter signal $\gamma_e = \gamma \rho|\eta|^2$. Thus, similar to the coherent receiver, the detection performance can be improved by either increasing the legacy system SNR $\gamma$ or the component $\eta_2$. In other words, when $\eta_2 = 0$, i.e., the direct path and the backscatter path are along the same direction, the noncoherent receiver has the worst performance. This fact suggests that the tag should not be placed on the direct path also for noncoherent receiver. One should also notice that $\eta_2$ can be controlled by the number of antennas $N_r$. Specifically, as $N_r$ increases, the area where $\eta_2 = 0$ shrinks.

VI. SIMULATION RESULTS
In this section, simulation results are provided to validate the performance of the proposed receiver. The distances are wavelength-scaled in order to make the result carrier-frequency-independent. All the results are obtained by averaging over $10^6$ Monte Carlo realizations. In the following, we first evaluate the performance of the proposed ML-assisted receiver with different parameters to show their impact. Then, we compare the performance of the ML-assisted method with...
the traditional receivers. Finally, we provide the variation in the performance with the tag location to show the expected coverage area for a single-tag deployment.

A. Numerical Evaluation

We consider a linear antenna array at the Rx with half-wavelength $\lambda/2$ antenna separation. The Tx and Rx are separated by the distance $d_{01} = 80\lambda$ as shown in Fig. 1. We consider the narrow angular spread of multipath for both the direct path and the backscatter path so that each component of the Rx antenna sees the fading process in the same manner. Unless otherwise specified, we model the direct path channel as Ricean fading channel with $K$-factor $K_0 = 5$, and model the links of Tx-Tag and Tag-Rx of the backscatter path channel as Ricean fading channel with $K$-factor $K_2 = 5$, $K_1 = 10$, respectively. The averaged power difference of the direct path and backscatter path channel are as in (1). The scattering efficiency caused by the tag modulator is $\rho = 0.6$ ($-2.2\, \text{dB}$).

Let $\Delta_e = \gamma_e/\gamma = \rho |\eta_2|^2$ be the power difference between the effective backscatter signal and the direct path signal. The variation in $\Delta_e$ in dB as a function of tag location for $N_r = 10$ is plotted in Fig. 8. It can be seen that when the tag is far away from both the Tx and Rx, the backscatter path undergoes a tremendous power loss, nearly $-60\, \text{dB}$. Even with a short distance $d_{11} \approx 2\lambda$, $\Delta_e$ reaches over $-40\, \text{dB}$. This result implies that the averaged effective SNR of the backscatter signal $\gamma_e$ is usually less than $0\, \text{dB}$ even when the SNR of the ambient signal is $\gamma = 30\, \text{dB}$. Moreover, there exists a null beam on the line segment between the Tx and the Rx. One can predict that the receiver fails to detect the backscatter signal from the tag placed inside the null beam as $\eta_2$ is extremely small. However, the null beam will become narrower as $N_r$ increases.

Hereafter, the incident angle between the backscatter path and the antenna array is fixed to $\pi/4$ radians but with varying distance $d_{11}$, i.e., the tag location is $p = [(d_{01}/2) - d_{11}/\sqrt{2}, d_{11}/\sqrt{2}]$. The ambient signal samples are generated from zero-mean Gaussian distribution with average transmit power $N_r/\gamma$, which is a practical assumption for signals with complex modulations, such as, OFDM signal.

The BER performance of the proposed ML-assisted method for the BPSK-modulated tag signal with different parameters is shown in Fig. 9. In Fig. 9(a) and (b), the variations of BER of the ML-assisted method with different numbers of antennas $N_r$ are compared. The values of effective SNR $\gamma_e$ and the corresponding values of legacy system SNR $\gamma$ are shown on the bottom and top $x$-axis, respectively. The coding scheme is not used and the preamble size is set to $L = 64$. The result clearly shows that the improvement of increasing the number of receiver antennas is diminishing as $N_r$ becomes larger. This is consistent with the error probability of spatial diversity [43, Sec. 3.3]. Considering this result, in the following, we fix $N_r = 10$.

The effect of coding on SER as a function of code order $r$ is shown in Fig. 9(b) for the effective SNR of backscatter signal $\gamma_e \approx -2\, \text{dB}$ and the preamble size $L = 64$. In this figure, we compare the performance of the Ricean fading channels with $K_0 = 5$, $K_1 = 10$ and $K_2 = 5$ with a worse situation where the LOS component does not exit for the link of Tx-Rx and the link of Tx-Tag, i.e., $K_0 = K_2 = 0$. It can be seen that using longer codewords improves the BER performance as longer codewords can correct more errors. As the channels become worse, however, an acceptable SER will be obtained at the expense of increasing $r$. Furthermore, using the Hadamard code and the Simplex code obtains a similar performance under the same condition. Since Simplex code has one dimension less than Hadamard code, it has a higher energy per bit.
BPSK modulation has more information. The results indicate that increasing the preamble size improves the BER since longer preambles provide more samples for training the classifiers as well as for the direction estimators of $a$ and $c$. However, the improvement becomes minor when $L > 50$. In addition, a longer training sequence consumes more energy of the tag and adds computational complexity at the Rx. Hence, it is reasonable to choose $L = 50$. The performance difference between LDA and LR becomes larger as the effective SNR increases. This is because LDA works under the assumption of the Gaussian distribution, which is not true in our case as has been elaborated on in Section V. The soft margin SVM and LR have similar performance. As soft margin SVM requires tuning of a hyperparameter, LR is preferable among the studied ML algorithms.

**B. Performance Comparison**

In Fig. 10, the performance of the proposed ML-assisted receiver, the noncoherent receiver, and the coherent receiver as a function of effective SNR $\gamma_e$ is compared for both OOK and BPSK modulations. In this figure, the numerical results are obtained with perfect channel information to validate the derived error probabilities. The coding technique is not used. Values of the corresponding legacy system SNR $\gamma$ are shown on the top x-axis which indicates that the power difference $\Delta_e \approx -29.8$ dB. Solid lines are the error probabilities of the conventional receivers analyzed in Section V, while dashed lines with the same markers are their corresponding numerical results. It is observed that BPSK modulation has more than 6-dB gain compared with the OOK modulation. For OOK modulation, the noncoherent receiver does not work in low SNR region and it outperforms the coherent receiver as SNR increases. This is because the coherent receiver coarsely estimates the ambient signal whereas the noncoherent receiver considers its signal space. For both modulations, the proposed ML-assisted receiver performance, marked by dotted line, is close to the performance of the coherent receiver with a known phase offset which provides a lower bound of the error probability. As shown by the dashed line with marker (+), ignoring the phase offset degrades the detection performance where the degradation is increasing with the SNR. The result shows that it is necessary to take into account the phase offset, and the proposed receiver sufficiently mitigates its adverse impact.

**C. Coverage Area**

In Fig. 11, variation in the proposed receiver SER performance in the log scale for code order $r = 3$ and legacy system SNR $\gamma = 30$ dB is shown to gain a perspective of the coverage area of a single-tag deployment. The tag is placed within a $(110\lambda \times 40\lambda)$ area in which the Tx and Rx are placed at $p_t = [-40\lambda, 0]$ and $p_r = [40\lambda, 0]$, respectively. The SER increases as both the distance between the tag and Tx, and the distance between the tag and Rx increase, which is coherent with the result in Fig. 8. As can be seen from the figure, there is a null beam, i.e., worse SER, on the line between the Tx and Rx. In this area, $a$ and $h$ are inseparable, which gives rise to the fact that the backscatter path is also canceled while nullifying the direct path inference. The shape of the coverage area close to the Rx is caused by the symmetric linear antenna array. The result shows the coverage area is in the close vicinity of the Tx and a large region ($\sim 20\lambda$) around the Rx.

**VII. Conclusion**

In this article, the coherent reception of the BPSK-modulated tag signal in AmBC systems was studied. A coherent receiver was designed to realize the optimum correlation receiver. The receiver utilizes multiple antennas to mitigate the strong DPI and the rapidly varying ambient signal and uses
LR algorithm to tackle the challenging phase offset caused by the excess length of backscatter path. The designed receiver achieves the same BER performance with 1-dB more SINR compared to the derived error probability of the optimum correlation receiver and outperforms the noncoherent receiver. This work suggested that a multiantenna receiver can effectively mitigate the direct-path interference and enable coherent demodulation of the tag signal, which has not been reported in the literature. The receiver performance is defined by the legacy system SNR and tag location. The spatial performance variation shows that the coverage area of a single tag deployment is in the close vicinity of the transmitter and within 20 wavelengths around the receiver. Consequently, a successful AmBC network deployment can be achieved by placing the receiver in a suitable location with respect to the location of the tags, and the distance between them can be further increased by using the presented coherent receiver.

**APPENDIX A**

**PROOF OF PROPOSITION I**

The demodulation of the BPSK-modulated tag signal is formed by a binary hypothesis testing, written as $H_{m} : x_{m}$ is transmitted, $m \in \{0, 1\}$. When the effective tag signal $u[i]$ is obtained, the binary hypothesis test of the optimum receiver is built upon the MAP criterion

$$p(x_{0}|u[i]) \cong p(x_{1}|u[i])$$

where $p(x_{m}|u[i])$ is the posterior probability of $x_{m}$ given the effective backscatter signal. According to Bayes’ theorem, the MAP criterion is written as

$$p(x_{0})p(u[i]|x_{0}) \cong p(x_{1})p(u[i]|x_{1})$$

$$p(u[i]|x_{0}) \cong p(u[i]|x_{1})$$

(13)

where $p(u[i])$ is irrelevant for making a decision of $x_{m}$, and $x_{m}$ have equal probability such that the MAP criterion becomes the maximum likelihood criterion. The likelihood function $p(u[i]|x_{m})$ contains a hidden variable, i.e., the ambient signal $s$. If the statistical information of the unknown $s[i]$ is provided, we can calculate $p(u[i]|x_{m})$ by integrating the joint distribution over the ambient signal space. In our case, the ambient signal can be partially estimated as

$$\hat{s}[i] = a^{H}y[i].$$

We can now rewrite $p(u[i]|x_{m})$ as

$$p(u[i]|x_{m}) = \int p(u[i], s|x_{m})ds$$

$$= \int p(u[i]|s, x_{m})p(s)ds = p(u[i]|s = \hat{s}[i], x_{m}).$$

The last equality holds since the ambient signal is coarsely estimated such that $p(s[i] = \hat{s}[i]) = 1$. Substituting it into (13) yields

$$p(u[i]|s = \hat{s}[i], x_{0}) \cong p(u[i]|s = \hat{s}[i], x_{1})$$

$$= |u[i] - \sqrt{e^{i\phi}}\hat{s}[i]x_{0}|^2 H_{0} \cong |u[i] - \sqrt{e^{i\phi}}\hat{s}[i]x_{1}|^2$$

$$\Re\{e^{-j\phi}y[i]^{H}ac^{H}y[i|x_{0}]\} \cong \Re\{e^{-j\phi}y[i]^{H}ac^{H}y[i|x_{1}]\}$$

where the common real coefficient $2\sqrt{e}$ is canceled out.

**APPENDIX B**

**DISTRIBUTION OF TEST STATISTIC**

The received signal $y$ given $x_{m}$ can be written as

$$y|x_{m} = R_{y|x_{m}}^{1/2}v$$

where $v \sim CN(0, I)$ is a standard circularly symmetric complex Gaussian random vector. The covariance matrix when $x = x_{m}$ is

$$R_{y|x_{m}} = E\{yy^{H}|x_{m}\}$$

$$= \gamma \cdot \left(1 + \rho|\eta_{1}|^2|x_{m}|^2 + \sqrt{\rho}\eta_{1}x_{m} + \sqrt{\rho}\eta_{1}^{*}x_{m}^{*}\right)\alpha a^{H}$$

$$+ \left(\rho|\eta_{2}|^2|x_{m}|^2 + \sqrt{\rho}\eta_{2}x_{m} + \sqrt{\rho}\eta_{2}^{*}x_{m}^{*}\right)\alpha c^{H}$$

$$+ \left(\rho|\eta_{1}|^2|x_{m}|^2 + \sqrt{\rho}\eta_{1}x_{m} + \sqrt{\rho}\eta_{1}^{*}x_{m}^{*}\right)\epsilon e^{H} + \epsilon e^{H} + \epsilon e a^{H} + \epsilon e c a^{H}$$

which is a full rank matrix. Then, $\xi$ conditioned on $x = x_{m}$ can be rewritten as

$$\xi|x_{m} = v^{H}R_{y|x_{m}}^{-1/2}MR_{y|x_{m}}^{1/2}v.$$

(14)

Using the result from Al-Naffouri et al. [44], it is known that the distribution of the quadratic form over the Gaussian random variables is dependent on the eigenvalues of $R_{y|x_{m}}^{-1/2}MR_{y|x_{m}}^{1/2}$. Now, since the nonzero eigenvalues of matrices $AB$ and $BA$ are the same [45, Th. 1.3.22], the nonzero eigenvalues of $R_{y|x_{m}}^{-1/2}MR_{y|x_{m}}^{1/2}$ can be calculated from matrix $M$ defined as

$$M = R_{y|x_{m}}^{-1/2}MR_{y|x_{m}}^{1/2} = e_{1}\alpha a^{H} + e_{2}\epsilon e^{H} + e_{3}\alpha c^{H} + e_{3}\epsilon e^{H} + e_{3}\epsilon e^{H}$$

(15)

where

$$e_{1} = \frac{\gamma}{2} \left(\rho|\eta_{1}|^2|x_{m}|^2 + \sqrt{\rho}\eta_{1}x_{m} + \sqrt{\rho}\eta_{1}^{*}x_{m}^{*}\right)$$

$$e_{2} = \frac{\gamma}{2} \left(1 + \rho|\eta_{2}|^2|x_{m}|^2 + \sqrt{\rho}\eta_{2}x_{m} + \sqrt{\rho}\eta_{2}^{*}x_{m}^{*} + 1\right)$$

$$e_{3} = \frac{\gamma}{2} \left(\rho|\eta_{1}|^2|x_{m}|^2 + 1\right).$$

Next, let us look at the rank of matrix $M$. It is easy to see the eigenvalue decomposition of matrix $M$ is

$$M = [u_{1} \quad u_{2}]\begin{bmatrix}0.5 & 0 \\ 0 & -0.5\end{bmatrix}\begin{bmatrix}u_{1} & u_{2}\end{bmatrix}^{H}$$

where

$$u_{1} = (a + e^{i\phi}c)/\sqrt{2} \quad \text{and} \quad u_{2} = (-e^{-i\phi}a + e)/\sqrt{2}.$$

Therefore, $M$ is a rank-2 matrix. According to the Sylvester inequality [45], the rank of matrix $M$ holds

$$\text{rank}(R_{y|x_{m}}^{-1/2}M) + \text{rank}(M) - N_{r} = 2 \leq \text{rank}(M).$$

Hence, matrix $M$ is also a rank-2 matrix.
The only remaining task is to obtain the eigenvalues of matrix $\mathcal{M}$. For this purpose, theorem [45, Th. 1.3.22] is invoked once again. Since (15) can be written as

$$\mathcal{M} = \begin{bmatrix} e_1 a + e_2 c & e_2 a + e_1 c \\ e_1 e_2^* & e_2 e_1^* \end{bmatrix} \begin{bmatrix} e_1^H \\ e_2^H \end{bmatrix},$$

its two nonzero eigenvalues are the same as the eigenvalues of the matrix written below

$$a^H \begin{bmatrix} e_1 a + e_2 c & e_2 a + e_1 c \\ e_1 e_2^* & e_2 e_1^* \end{bmatrix} a = \begin{bmatrix} e_1^2 \\ e_2^2 \end{bmatrix},$$

After performing several algebraic manipulations, the eigenvalues of $\mathcal{M}$ are

$$\lambda_\ell(x_m) = \varepsilon_m + (-1)\ell \sqrt{\varepsilon_m^2 + A_m}, \quad \ell \in \{1, 2\}. \tag{16}$$

It is worth mentioning that $|\eta_1| \ll 1$ and $|\eta_2| \ll 1$ such that the eigenvalues expressed in (16) are dominated by $A_m$, which yields that $\lambda_1(x_m)$ is negative and $\lambda_2(x_m)$ is positive. With these two eigenvalues, the test statistic in (14) is an indefinite quadratic form of the Gaussian random variables whose distribution is given in [44]. For the studied case, the obtained test statistic follows the asymmetrical Laplace distribution (ALD), of which the CDF and PDF are as in (7a) and (7b), respectively.

In addition, $\varepsilon_m$ is dominated by $\text{Re} \{\gamma \sqrt{\rho_1 \rho_2} \eta_1^2 |x_m|^2 + \sqrt{\rho_1} \rho_2 \}$, and $A_m$ is dominated by the $\gamma/4$ term, which does not rely on $x_m$ so $A_0$ and $A_1$ have similar values. The expectation and variance of ALD are

$$E[\xi |x_m|] = -\lambda_1(x_m) - \lambda_2(x_m) = -2\varepsilon_m \tag{17a}$$

$$\text{Var}[\xi |x_m|] = \lambda_1^2(x_m) + \lambda_2^2(x_m) = 4\varepsilon_m^2 + 2A_m^2 \tag{17b}$$

respectively. Therefore, when the tag adopts BPSK modulation, we have $E[\xi |x_0|] \approx -E[\xi |x_1|]$ and $\text{Var}[\xi |x_0|] \approx \text{Var}[\xi |x_1|]$. 

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