Blind Channel Estimation for Ambient Backscatter Communication Systems

Shuo Ma, Gongpu Wang, Rongfei Fan, and Chintha Tellambura

Abstract—**The availability of perfect channel state information (CSI) is assumed in current ambient-backscatter studies. However, the channel estimation problem for ambient backscatter is radically different from that for traditional wireless systems, where it is common to transmit training (pilot) symbols for this purpose. In this letter, we thus propose a blind channel estimator based on the expectation maximization (EM) algorithm to acquire the modulus values of channel parameters. We also obtain the ranges of the initial values of the suggested estimator and derive the modified Bayesian Cramér-Rao bound (MBCRB) of the proposed estimator. Finally, simulation results are provided to corroborate our theoretical studies.**

Index Terms—**Ambient backscatter, channel estimation, channel state information (CSI), expectation maximization (EM), Internet of Things (IoT).**

I. Introduction

INTERNET of Things (IoT) has attracted vast attentions from both academic and industrial circles. For wireless sensors or tags in IoT, two main challenges exist:

- **Limitations of Energy sources –** Batteries, the most common energy source for sensors, have limited operational life and thus require maintenance of recharging or replacement. Other sources including solar and wind energy are subjected to the vagaries of the environment.
- **Cost of radio frequency (RF) components –** The nodes will need oscillators, amplifiers and other RF components, which are expensive compared with the baseband circuits.

A potential solution to these two challenges is the emergence of ambient backscatter wireless technology [1]. A basic setup is shown in Fig. 1. First, the sensor node harvests wireless energy from ambient RF signals; second, the sensor switches the antenna impedance so as to backscatter outside or absorb inside the received RF signal, which indicates for the reader "1" or "0" state respectively. Harvesting energy from ambient RF sources (e.g., TV signals, AM and FM signals, cellular base stations, and Wi-Fi access points (APs)) is utilized. This approach can thus free sensors or tags from batteries and decrease the cost by removing the expensive active RF circuits. No dedicated frequency spectrum is required. These advantages open up the possibility of many practical IoT applications [2].

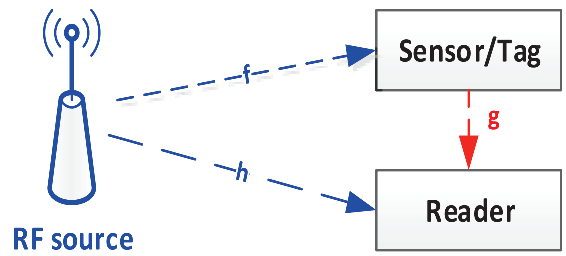

Fig. 1. System model.

Most of the existing ambient-backscatter studies assume the availability of perfect channel state information (CSI) or avoid the need for CSI through differential encoding techniques [3], [4]. In fact, ambient-backscatter channel estimation is complicated due to the following reasons:

1) the ambient RF signals are unknown to both the sensors/tags and the receivers/readers;
2) the sensors/tags are of simple design and subject to the constraint of limited harvested power, and usually cannot transmit training symbols;
3) the channel parameters when transmitting "1" are not consistent with those when transmitting "0" bits.

The traditional estimators are based on the principles of least square (LS) and linear minimum mean square error (LMMSE), where it is necessary to send pilot symbols for channel estimation [5], [6]. They cannot be directly applied in ambient backscatter systems. To the best of our knowledge, the problem of ambient-backscatter channel estimation has not been studied before, which motivates our current work.

In this letter, we design a new ambient-backscatter channel estimator and investigate its performance. Given these challenges, and especially because of not using pilot sequences, a blind estimation approach is necessary. We thus select the expectation maximization (EM) estimation algorithm [7] and obtain the absolute values of channel parameters. We also propose the ranges of initial values without requiring extra pilots. In addition, we derive the modified Bayesian Cramér-Rao bound (MBCRB) of the proposed estimator. Finally, simulation results are provided to assess the mean square error, MBCRB and the speed of convergence of our proposed algorithm.

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S. Ma and G. Wang are with Beijing Key Lab of Transportation Data Analysis and Mining, School of Computer and Information Technology, Beijing Jiaotong University, Beijing 100044, China. (e-mail: 16120405@bjtu.edu.cn; gpwang@bjtu.edu.cn).

R. Fan is with School of Information and Electronics, Beijing Institute of Technology, Beijing 100081, China. (e-mail: fanrongfei@bit.edu.cn).

Chintha Tellambura is with the Department of Electrical and Computer Engineering, University of Alberta, Edmonton AB, Canada, T6G 1H9. (e-mail: chintha@ece.ualberta.ca).

II. System Model

Consider an ambient backscatter communication system that consists of a reader, a tag, and an RF source (Fig. 1). Assume that the RF source transmits the signals $x(n)$ with power P_t, and the tag transmits binary information $B(n) \in \{0,1\}$ by backscattering the message $x(n)$ to the reader or by absorbing $x(n)$ inside. Suppose that the reader has no knowledge about $x(n)$ except the transmit power P_t.

Denote the channels between the RF source and the reader, between the tag and the RF source, and between the reader and the tag as h, f, and g, respectively. Suppose $h \sim \mathcal{N}(0, N_h)$ and $f \sim \mathcal{N}(0, N_f)$, where N_h and N_f represent the corresponding channel variances. The distance between the reader and the tag is short and typically line of sight (LOS), which renders the channel g approximately a constant.

The tag transmits $B(n)$ through backscattering its received source signal $x(n)$ or not. Suppose that the attenuation of the signal $x(n)$ inside the tag is η. The received signal $y(n)$ can be given as [3]

$$y(n) = \begin{cases} hx(n) + w(n), & B(n) = 0 \\ hx(n) + \eta f g x(n) + w(n), & B(n) = 1 \end{cases} \quad (1)$$

where $w(n)$ denotes the zero-mean additive white Gaussian noise (AWGN) with variance N_w at the reader. Define the combined channel parameter as

$$\mu = h + \eta f g. \quad (2)$$

Clearly, $\mu \sim \mathcal{N}(0, N_\mu)$ where $N_\mu = N_h + \eta^2 g^2 N_f$. One goal of the reader is to simultaneously estimate h and μ given data $y(n)$ with unknown $x(n)$ and $B(n)$.

Remark 1: The channel reciprocity holds in our model. However, we only focus on uplink channel in our paper.

Remark 2: In our model, the tag is a battery-free device and can not generate active radio signals. The distance between the tag and the reader is one key factor deciding the channel quality.

III. EM-based Channel Estimation

In this section, we will design an EM-based estimator to obtain the absolute values of the channel parameters h and μ.

The EM algorithm [7] is an iterative method to find maximum likelihood estimates of parameters when there are unobserved variables. It has two steps: (a) expectation of the log-likelihood evaluated using the current estimate for the parameters and (b) maximization of the log-likelihood derived in the expectation step to compute parameters. The EM iteration alternates between these two steps. The parameter estimates in each iteration are then used in the next expectation step. In the ambient backscatter estimation problem, we in fact will work with a lower bound of the log-likelihood function.

A. Channel Estimation

For brevity of our discussion, we assume that $x(n)$ has only two states x_1 and x_2, e.g., binary phase shift keying (BPSK) signal.[1]

[1] Our algorithm can be straightly extended to the case of $x(n)$ with multiple states such as multiple phase shift keying (MSPK) or multiple quadrature amplitude modulation (MQAM).

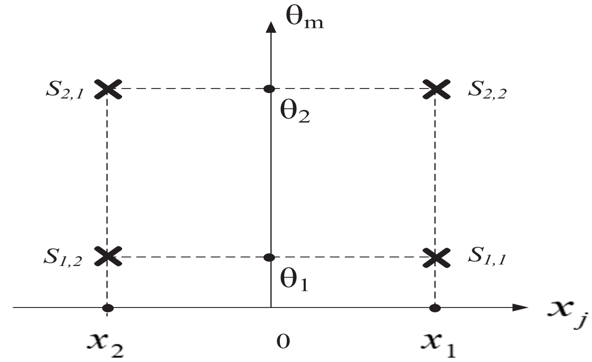

Fig. 2. Constellation of hidden variables and intermediate variables.

Let us first rewrite the signal $y(n)$ (1) as

$$y(n) = \theta_m x_j + w(n), \quad m, j = 1, 2 \quad (3)$$

where θ_m denotes the two channel parameters h and μ, and if $\theta_1 = h$ or $\theta_1 = \mu$ is to be determined.

Next we introduce the following two intermediate variables:

1) $S_{m,j}$ denotes the four combinations of x_j and θ_m as shown in Fig.2 where $m = 1, 2$ and $j = 1, 2$.
2) $Q_{m,j}(i)$ is the posterior probability for $S_{m,j}$ when the received signal is $y(i)$.

It can be readily checked that

$$Q_{m,j}(i) = p(S_{m,j}|y(i)) = \frac{f(y(i)|S_{m,j})\, p(S_{m,j})}{f(y(i))}, \quad (4)$$

where $f(y(i)|S_{m,j})$ denotes the conditional probability density function (PDF) of $y(i)$. Since both $x(n)$ and $B(n)$ are equiprobable, we have $p(S_{m,j}) = 0.25$. Thus the posterior probability $Q_{m,j}(i)$ can be further derived as

$$\begin{aligned} Q_{m,j}(i) &= \frac{f(y(i)|S_{m,j};\theta_m)\, p(S_{m,j})}{\sum_{m=1}^{2}\sum_{j=1}^{2} f(y(i)|S_{m,j};\theta_m)\, p(S_{m,j})} \\ &= \frac{e^{-\frac{(y(i)-\theta_m x_j)^2}{2\sigma^2}}}{\sum_{m=1}^{2}\sum_{j=1}^{2} e^{-\frac{(y(i)-\theta_m x_j)^2}{2\sigma^2}}}. \end{aligned} \quad (5)$$

Define $\theta_m^{(n)}$ as the value of θ_m at the nth iteration. The lower bound of the log-likelihood function of $\theta_m^{(n)}$ is

$$\widetilde{L}\left(\theta_m^{(n)}\right) = \sum_{i=1}^{N}\sum_{m=1}^{2}\sum_{j=1}^{2} Q_{m,j}(i) \ln \frac{f\left(y(i) \mid S_{m,j};\theta_m^{(n)}\right) p(S_{m,j})}{Q_{m,j}(i)}. \quad (6)$$

We compute the partial derivatives with respect to $\theta_1^{(n)}$ and $\theta_2^{(n)}$ respectively to update the estimates in the $(n+1)$th iteration

$$\theta_m^{(n+1)} = \frac{\partial \widetilde{L}}{\partial \theta_m^{(n)}} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{2} Q_{m,j}(i) x_j y(i)}{\sum_{i=1}^{N}\sum_{j=1}^{2} Q_{m,j}(i) x_j^2}. \quad (7)$$

Algorithm 1 Our proposed channel estimator

Input: $[y(1), \cdots, y(N)]$, P_t, $\tilde{h}$.
Output: CSI estimates $\hat{h}$, $\hat{\mu}$.
Initialization: according to (10) and (11).
Iteration:
while $\tilde{L}$ (6) does not converges **do**
  for i=1:N **do**
    update $Q_{m,j}(i)$ according to (5);
  end for
  update $\tilde{L}$ according to (6);
  update $\theta_1^{(n+1)}$ and $\theta_2^{(n+1)}$ through (7);
end while
if $|\theta_1^{(n+1)} - \tilde{h}| < |\theta_2^{(n+1)} - \tilde{h}|$ **then**
  $\hat{h} = \theta_1^{(n+1)}$;$\hat{\mu} = \theta_2^{(n+1)}$;
else
  $\hat{\mu} = \theta_1^{(n+1)}$;$\hat{h} = \theta_2^{(n+1)}$;
end if
return $\hat{h}$ and $\hat{\mu}$;

TABLE I
COMPUTATIONAL COMPLEXITY OF EACH ITERATION.

Steps	Computational complexity
Compute (5)	$N[3(1+MJ)+1]$
Calculate (6)	$5NMJ$
Update (7)	$M(4JN+1)$
Total complexity in each iteration	$12NMJ+4N+M$

Without loss of generality, we assume $|\theta_1| < |\theta_2|$. Let us introduce a new variable q defined as

$$q = \frac{\sum_{i=1}^{N} |y(i)|}{\sqrt{P_t}}. \tag{8}$$

The expectation of q can be found as

$$E(q) = \frac{E(|\theta_1|) + E(|\theta_2|)}{2} = \frac{\sqrt{N_h} + \sqrt{N_\mu}}{\sqrt{2\pi}}. \tag{9}$$

where $E|\theta_1| < E(q) < E|\theta_2|$.

Proposition 1: Define $P_{th} = 9\pi N_w/(2(\sqrt{N_h} + \sqrt{N_\mu})^2)$. The initial values of $\theta_m^{(0)}$ can be set as

$$\theta_1^{(0)} = q - \epsilon, \quad \theta_2^{(0)} = q + \epsilon. \tag{10}$$

where ϵ is a constant that satisfies

$$\begin{cases} 0 < \epsilon < q, & \text{if } P_t \leq P_{th} \\ \sqrt{N_w/P_t}/2 < \epsilon < q - \sqrt{N_w/P_t}, & \text{if } P_t > P_{th}. \end{cases} \tag{11}$$

Proof: In high SNR, it is desirable that the gap between the two initial values is large. Therefore, we can have

$$|2\epsilon x_j| > E|w(n)|, \quad |\theta_m^{(0)} x_j| > E|w(n)|. \tag{12}$$

After averaging both sides of (12), we can obtain $\epsilon \in (\sqrt{N_w/P_t}/2, q - \sqrt{N_w/P_t})$. Further utilizing $q - \sqrt{N_w/P_t} \geq \sqrt{N_w/P_t}/2$, we can obtain the expression of P_{th}. ■

Our proposed estimator is summarized in Algorithm 1. It includes three inputs: received data $y(n)$, transmit power P_t, and the estimate $\tilde{h}$ of the channel parameter $|h|$ through traditional EM algorithm before tag transmission.

B. Complexity Analysis

The time complexity of our proposed channel estimator is due to (a) three steps in each iteration and (b) the total number of iterations T. The computational complexity per iteration arises mainly from the three sub-steps: computing (5), calculating (6) and updating (7) (Table III-A.)

Thus, the total complexity of the proposed algorithm is $T(12NMJ + 4N + M)$ where M denotes the number of parameters and J denotes the number of states of the signal $x(n)$. In our case, $M = 2$ and $J = 2$. Thus, the complexity of each iteration is $\mathcal{O}(N)$ and the total complexity of our estimator can be approximated as $\mathcal{O}(TN)$.

C. Modified Bayesian Cramér-Rao bound (MBCRB)

The modified Bayesian Cramér-Rao lower bound (MBCRB) is a lower bound of MSE when the observed data depend on other nuisance parameters [9] and the channel estimates are random variables with a priori information available [8]. The MBCRB of the channel h is the inverse of ψ_h defined as

$$\psi_h = E_h[G(h)] + E_h\left[-\frac{\partial^2 \ln f(h)}{\partial h^2}\right], \tag{13}$$

where $f(h)$ is the PDF of h and $G(h)$ is the modified Fisher Information Matrix (FIM)

$$G(h) = E_{\mathbf{S}} E_{\mathbf{y}|\mathbf{S},h}\left[-\frac{\partial^2 \ln f(\mathbf{y}|\mathbf{S};h)}{\partial h^2}\right]$$
$$= \sum_{i=1}^{N}\sum_{j=1}^{2} p(S_{m,j})\left(E_{y_i}\left[-\frac{\partial^2 \ln f(y_i|S_{m,j};h)}{\partial h^2}\right]\right) = \frac{NP_t}{2N_w}.$$

The second term of (13) can be obtained as

$$E_h\left[-\frac{\partial^2 \ln f(h)}{\partial h^2}\right] = \frac{1}{N_h}. \tag{14}$$

Consequently, the MBCRB of h can be obtained as

$$M_h = \frac{2N_w N_h}{NP_t N_h + 2N_w}. \tag{15}$$

Similarly, the MBCRB of μ can be found as

$$M_\mu = \frac{2N_w N_\mu}{NP_t N_\mu + 2N_w}. \tag{16}$$

IV. Simulation Results

In this section, we provide numerical results of the proposed estimator. The attenuation η is set to 0.8 and the variances N_h, N_f and N_w are set to 1.

Fig. 3 depicts the MSE and MBCRB curves versus SNR when the signal length N=10. For each SNR, we choose the initial values (11), estimate the channels h and μ utilizing Algorithm 1, and calculate the corresponding MSE and MBCRBs (15) and (16). This figure shows that the simulated MSEs converge to theirs MBCRBs when the SNR is sufficiently high. The gap between the two curves for the case of estimation of μ is very small. However, the gap for the case of estimation of h is fairly large and persistent, and this may be due to the use of blind estimation [10].

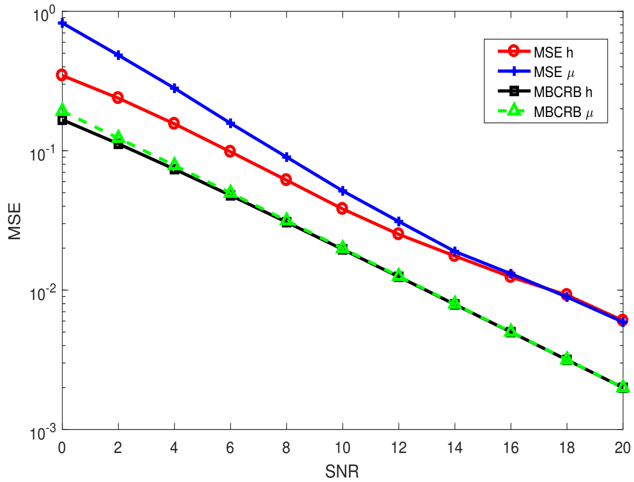

Fig. 3. MSE and MBCRB versus SNR.

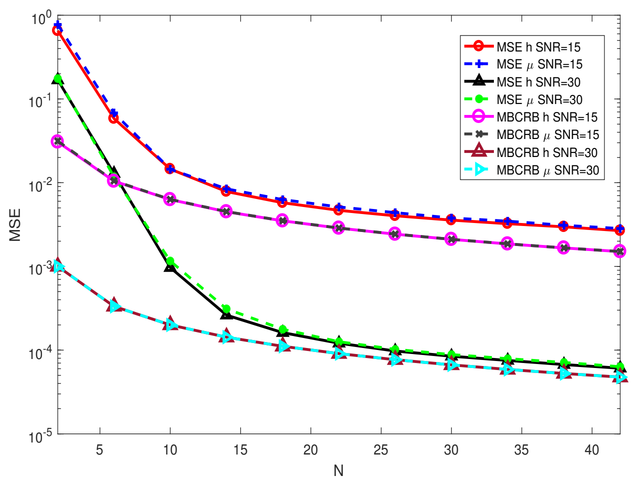

Fig. 4. MSE and MBCRB versus signal lengths N.

Fig. 4 plots the MSE and MBCRB curves versus different signal lengths N when SNR is 15 dB and 30 dB respectively. Both MSE and MBCRB decline with larger N. The MSE gains from increasing N are small when $N > 20$.

Fig. 5 shows the the number of iterations when the signal length N is 10, 20, and 30 respectively. It can be seen that the average number of iterations decreases rapidly when SNR increases, and that our proposed estimator needs only three iterations for an SNR of 20 dB.

V. Conclusion and Future work

This letter investigated the channel estimation problem for ambient backscatter communications. Specifically, an EM-based estimator was proposed to obtain the modulus values of the ambient backscatter channel parameters. The ranges of initial values were suggested for the proposed estimator. To assess the quality of the estimates, the The modified Bayesian Cramér-Rao lower bounds were derived. Finally, numerical results were provided to corroborate our theoretical results.

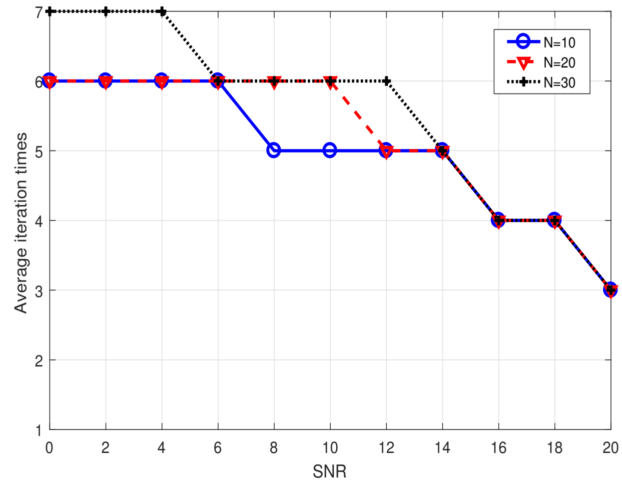

Fig. 5. The number of the iterations for the proposed algorithm.

Regarding ambient-backscatter channel estimation, the work reported in this letter is just the tip of the iceberg because there are many open problems [2]. For example, channel estimates are needed for optimal backscatter scheme at the tag, multiple tag access and tag selection by the reader. Moreover, the estimation of individual channel parameters f and g can also be a fruitful future research since these parameters play a fundamental role in transceiver design and security enhancement [11].

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