DEEP LEARNING BASED PASSIVE BEAMFORMING FOR IRS-ASSISTED MONOSTATIC BACKSCATTER SYSTEMS

(Invited Paper)

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ABSTRACT

Intelligent reflecting surfaces (IRS) can improve the performance of backscatter communication systems by employing reconfigurable phase shifts (or passive beamforming) to favorably configure the wireless propagation medium. However, the design of optimal IRS phase shifts requires channel state information (CSI), which is hard to acquire in a multi-reflection channel. In this paper, we propose a deep learning based framework that learns the desired IRS phase shifts without knowing the channels, to assist the communication of a passive backscatter tag. This is achieved by parameterizing the mapping from the received pilots to the desired configuration of IRS by training a deep neural network (DNN) *BIRS-Net* on a sufficiently large dataset covering a variety of channel realizations and possible power splitting ratios at the backscatter tag. Simulation results show that the proposed DNN based solution can efficiently learn to maximize the SNR of backscatter transmission and exhibits near optimal performance.

***Index Terms*—** Backscatter communication, deep learning, intelligent reflecting surface, energy harvesting, passive beamforming.

1. INTRODUCTION

Backscatter communication (BackCom) has been envisaged as promising technology to realize energy efficient connectivity for the self-sustainable Internet of Things (IoT) [1]. BackCom devices or tags are typically low-cost passive devices that reflect and modulate incident radio frequency (RF) signals via intentional impedance mismatch, while harvesting energy from the incident signals to power their own operation [2]. However, despite the recent uptake of research in this area, the issues of limited range and low achievable bit rate continue to exist.

Intelligent reflecting surface (IRS) has recently emerged as a transformative technology that can tailor the wireless propagation environment by the coordinated design of phase shifts at its reflectors (passive beamforming), to ensure constructive or destructive reception at desired locations in the network [3–5]. The anticipated widespread integration of IRS in future wireless networks has motivated exploration of the potential enhancement of BackCom and other 6G technologies by leveraging an IRS located nearby [6–9]. In particular, the IRS can favorably assist monostatic BackCom by enhancing the effective gain of both the reader to tag (forward) and the tag to reader (backscatter) links [10, 11].

To leverage the passive beamforming gain of the IRS, channel state information (CSI) is needed. CSI acquisition in this case is challenging due to the passive reflecting nature of both these technologies and because only the composite channel (cascade of forward and backscatter links) is observable at the reader. Moreover, each of the forward and backscatter channels is a sum of the direct and via IRS links. Thus, the channel estimation techniques proposed for other IRS-assisted systems [12, 13] or for BackCom only systems [14] are not applicable in this case. Besides, once the channels are known, the optimized IRS phase shifts need to be obtained based on the estimated channels. Owing to recent advances in deep learning (DL), an explicit CSI acquisition step can be skipped and the passive beamforming can be directly obtained using data driven techniques. This is evidenced by the success of several DL based frameworks including the sum-rate maximization in an IRS assisted multi-user MIMO system without explicit channel estimation by employing a DL framework proposed in [15] and an unsupervised learning based approach for passive beamforming in IRS-assisted communication systems [16].

In this work, we propose a DL based approach to address the problem of configuring the IRS phase shifts to assist a monostatic BackCom system located in its proximity. Moreover, our scheme also proposes the best value for the power splitting ratio of the tag to support the maximization of backscatter signal strength received at the reader while ensuring that the tag harvests enough power to sustain its operation. To the best of our knowledge, this is the first work to provide a learning-based end-to-end solution to the joint design of IRS reflection pattern and tag splitting ratio in an IRS-assisted BackCom system. Importantly, the solution does not

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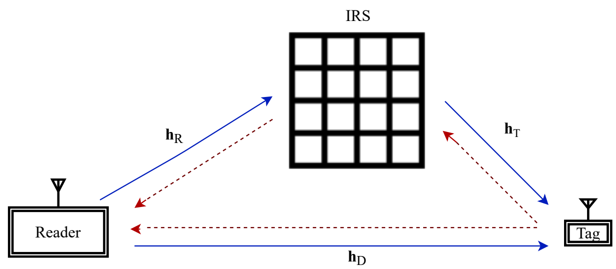

Fig. 1. Illustration of the system model.

involve explicit channel estimation. In this context, our main contributions are:

- We present a pilot-based training protocol and the associated optimization problem for maximizing the effective SNR γ_b of the backscatter transmission.
- We propose a DNN based solution named *BIRS-Net*, which maps the received pilots directly to the optimal IRS phase shifts and tag power splitting ratio, with the objective of maximizing γ_b. We discuss the DNN's implementation, training and tuning of hyper-parameters and its testing on unseen data.
- Our results indicate a near-optimal performance in maximizing the SNR of the backscatter transmission when BIRS-Net is deployed at the reader.

2. SYSTEM MODEL

We consider a monostatic BackCom system assisted by an IRS with N passive reflecting elements located nearby. The system consists of a full-duplex single-antenna reader and a single antenna backscatter tag. We model the system in a three dimensional setup as shown in Fig. 1.

The IRS is assumed to be equipped with its own power supply and a smart controller, which is connected to the reader via a separate reliable wireless link and is responsible for coordinating their operation as well as exchanging information such as reflection coefficients. As the tag performs diffuse reflection, we ignore the signals reflected two or more times at the tag due to severe power loss [17]. However, for the paths in which IRS is involved, it is necessary to consider the signals that undergo two reflections at the IRS, i.e., the signal going through the reader-IRS-tag-IRS-reader link [7].

The pathloss from the reader to tag is represented by $\beta_{\text{R-T}}$, while the pathloss of the reader-IRS-tag link is represented by $\beta_{\text{R-I-T}}$. We assume all the channels to be quasi-static, frequency non-selective and constant in each fading block with independent and identically distributed (i.i.d.) Rician fading. Let $h_{\mathrm{D}} \in \mathbb{C}$, $h_{\mathrm{R}} \in \mathbb{C}^{N\times 1}$ and $h_{\mathrm{T}} \in \mathbb{C}^{N\times 1}$ denote the baseband equivalent channels from the reader to tag, reader to IRS, and tag to IRS, respectively. If the signal sent out by the reader is denoted by x, then the overall signal received at the tag over both the direct and IRS reflecting links is given by

$$x_{\mathrm{T}} = \left(\sqrt{\beta_{\text{R-T}}} h_{\mathrm{D}} + \sqrt{\beta_{\text{R-I-T}}} \mathbf{v}^H \phi_{\text{R-I-T}}\right) x, \tag{1}$$

where $\phi_{\text{R-I-T}} = \operatorname{diag}(h_{\mathrm{R}}) h_{\mathrm{T}}$ and $\mathbf{v} = \left[e^{j\theta_1}, \ldots, e^{j\theta_N}\right]^T$ represents the reflection vector of the IRS such that $|v_n| = 1,\ \forall n \in \{1, \ldots, N\}$ and $\theta_n \in [0, 2\pi)$. Then, based on channel reciprocity (which is an accepted standard in monostatic backscatter systems [11, 14]), the backscattered signal from the tag, received at the reader is given by,

$$y_{\mathrm{R}} = \sqrt{\alpha}\ \ b\left(\sqrt{\beta_{\text{R-T}}} h_{\mathrm{D}} + \sqrt{\beta_{\text{R-I-T}}} \mathbf{v}^H \phi_{\text{R-I-T}}\right)^2 x + n, \tag{2}$$

where α is the power splitting coefficient of the tag and represents the fraction of the incoming signal to be reflected, while the fraction $1-\alpha$ of the signal energy is used to power the tag circuit, b is the information symbol of the tag, $n \sim \mathcal{CN}(0, \sigma^2)$ is the AWGN and σ^2 is the noise power.

We consider a two-phase data transmission protocol, where each channel coherence block of T symbols is divided into two phases. During the first pilot transmission phase of duration T_p seconds, the tag does not send any information and is kept fixed at a known state $\alpha = \alpha_0$ with $b = 1$. The reader transmits pilot symbols and receives back after they pass through the channel, undergoing backscatter at the tag and reflection by the IRS. These pilots are then used to obtain the best IRS passive beamforming $\mathbf{v}^*$ and the best value of the power splitting ratio at the tag α^* for backscatter data transmission. The reader communicates α^* to the tag and $\mathbf{v}^*$ to the IRS controller via separate links, so that the tag's backscatter communication in the second data transmission phase of duration $T - T_p$ seconds, can be facilitated.

3. PROPOSED TRAINING DESIGN AND PASSIVE BEAMFORMING PROTOCOL

During the training phase of duration $T_p = NK\tau_p$ seconds, the reader sends out pilot sequences. Since there are N values of IRS reflection coefficients to be estimated, we propose to turn the IRS elements ON one at a time and send a pilot sequence of length K for each element. Thus, for each of the N IRS reflection coefficients to be estimated, only one corresponding IRS element is turned ON while the rest of the IRS is kept OFF for a duration of $K \times \tau_p$ seconds. So when the i-th IRS element is turned on, i.e., $\mathbf{v} = [0, \ldots, v_i, \ldots, 0]^T$, the reader sends out the pilot sequence $\mathbf{x}_{\mathrm{P}i} = [x_{\mathrm{P}i}(1), x_{\mathrm{P}i}(2), \ldots, x_{\mathrm{P}i}(K)]$ of length K, with τ_p being the duration of each symbol in the sequence. Each such pilot sequence is sent out by the reader, backscattered by the tag and then received back at the reader as $\mathbf{y}_{\mathrm{R}i}$ while undergoing reflections at the IRS on the forward as well as backward path.

The $N \times K$ pilots are received at the reader, stored as a vector $\mathbf{y}_{\mathrm{R}} \in \mathbb{C}^{NK\times 1}$. Since the ultimate goal is to find the IRS reflection pattern $\mathbf{v}$ and the tag splitting ratio α that best facilitates the backscatter transmission, we propose to skip the explicit channel estimation and in turn directly employ the received pilots to obtain these. In particular, the problem of obtaining the mapping from the received pilots $\mathbf{y}_{\mathrm{R}}$ to the optimized IRS reflection pattern $\mathbf{v}^*$ and the tag splitting ratio α^* for maximizing the received SNR γ_b for the backscatter signal can be mathematically written as:

$$\mathcal{P}: \max_{\substack{\mathbf{v}=\mho(\mathbf{y}_{\mathrm{R}}),\\ \alpha=\eth(\mathbf{y}_{\mathrm{R}})}} \quad \gamma_b(\mathbf{v},\alpha) \tag{3a}$$

$$\text{s.t.} \quad |v_n| = 1,\ \forall n \in \{1,2,\dots N\}, \tag{3b}$$

$$0 \le \alpha \le 1, \tag{3c}$$

$$(1-\alpha)\eta \left|\sqrt{\beta_{\text{R-T}}}h_{\mathrm{D}} + \sqrt{\beta_{\text{R-I-T}}}\mathbf{v}^H\phi_{\text{R-I-T}}\right|^2 \ge \zeta, \tag{3d}$$

where $\mho$ and $\eth$ are functions that map the received pilots to the IRS phase shifts and the power splitting ratio at the tag respectively. (3d) is the circuit power constraint of the tag. This is a variational optimization problem, where the optimization variables are functionals. Moreover, the objective function and the constraints are highly non-convex. Since it is difficult to analytically solve such problems, we leverage the universal approximation property of the neural networks [18] and propose a DNN based solution named *BIRS-Net* to solve this problem and learn the mapping functions from received pilots to the optimal IRS phase shifts and the optimal value of the tag splitting ratio.

4. DEEP LEARNING FRAMEWORK

This section details the proposed deep learning based framework *BIRS-Net* to solve the problem $\mathcal{P}$ for the IRS-aided backscatter communication scenario outlined in the previous sections. *BIRS-Net* is a DNN consisting of fully connected layers, that parameterizes the mapping from the received pilots to the optimal IRS reflection pattern and the optimal tag splitting ratio. It takes the vectorized received pilots as inputs, and outputs the intended IRS phase shift vector $\mathbf{v}^*$ and the tag splitting ratio α^* that maximize the received SNR of the backscatter signal at the reader. *BIRS-Net* is trained offline and then deployed at the reader to estimate the best IRS reflection pattern and tag splitting ratio based on the incoming pilots. In the following, we discuss its structure, function, training procedure, and online deployment.

4.1. Structure of DNN

BIRS-Net consists of four fully-connected (FC) hidden layers with n_s neurons in each layer, where n_s is twice the dimension of the input feature vector, which in turn depends upon the IRS size as explained in Section 4.2. The purpose of setting the number of neurons proportional to N is to ensure adequate learning ability as the system scales. The activation function used for each fully connected layer is the hyperbolic tangent (tanh) activation function. A BatchNormalization (BN) layer is used after each fully connected layer. The output layer is a regression layer.

4.2. Training the DNN

The proposed DNN needs to be trained offline with a dataset comprising received pilots under a wide range of instances of channels and tag splitting ratios. Essentially, we compute a set of channels with known coefficients, based on which we generate the optimal IRS phase shifts using the closed form solution from [19] (which requires CSI knowledge) and the optimal tag splitting ratio by exhaustive search. Then we process the pilot signals through the system to obtain received pilots at the reader. The DNN uses supervised learning and hence the dataset needs to be organized in input-output pairs $\{\mathbf{I},\mathbf{O}\}$. The received pilots at the reader comprise the input to the DNN and the corresponding optimal IRS phase shifts and the optimal tag splitting ratio are the desired outputs that the DNN needs to learn. Since the existing deep learning modules do not support complex number operations, the received pilots are split into their real and imaginary parts and stacked such that the input to the neural network $\mathbf{I} = [\Re(\mathbf{y}_{\mathrm{R}}), \Im(\mathbf{y}_{\mathrm{R}})]^T$. Thus, the dimension of the input feature vector in $2NK$. Similarly for the output data, the real and imaginary parts of the optimal IRS phase shift vector are stacked and then appended with the optimal splitting ratio, i.e., the output is of the format $\mathbf{O} = [\Re(\mathbf{v}^*), \Im(\mathbf{v}^*), \alpha^*]^T$. The input and output vectors are then cast into cell arrays and used in sequence-to-sequence regression for training and testing phases. The loss function of the DNN is given by [20]

$$\mathcal{L}(\mathbf{\Theta}) = \frac{1}{B}\sum_{m=1}^{B} ||\hat{\mathbf{O}}(m) - \mathbf{O}(m)||_2^2 + \lambda \sum_{m=1}^{B} {\Theta_m}^2 \tag{4}$$

where $\hat{\mathbf{O}}$ are the predictions of the DNN and $\mathbf{O}$ are the true values of the output, Θ is the set of learnable parameters being updated during training and B is the mini-batch size. The λ term in the loss function represents L2 regularization to address the issue of over-fitting.

To train the network, adam optimizer is used. The number of training epochs required for the *BIRS-Net* to train depends upon the IRS size. An early stopping criterion is also applied that stops the training when the validation accuracy does not improve in several consecutive epochs. To avoid overfitting, in addition to L2 regularization, a dropout of 10% is used. Moreover, the training data is shuffled at every epoch to ensure better generalization of the DNN.

5. RESULTS

In this section, we present the numerical results. The reader emits continuous wave at a frequency of $f_c = 915$ MHz and transmit power normalized to 1. The reader, tag and IRS are

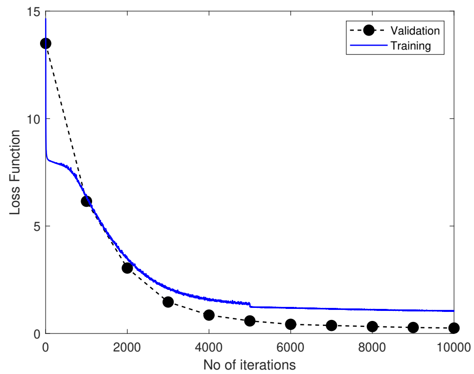

Fig. 2. Training progress for *BIRS-Net* for $N = 16$.

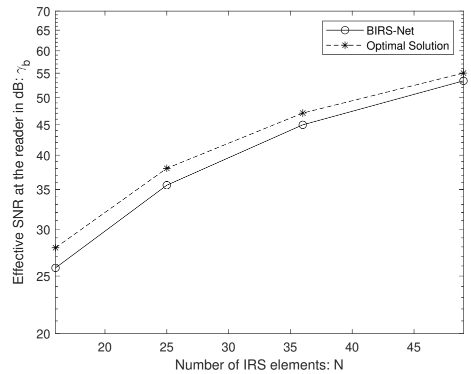

Fig. 3. Impact of the IRS size on the effective SNR of the backscatter link.

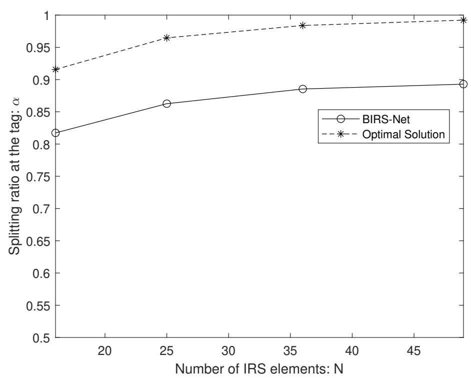

Fig. 4. Impact of the IRS size on the tag splitting ratio.

located at $[5, 0, 0]$, $[5, 12, 0]$ and $[5, 20, 1]$ respectively, with all the 3-D coordinates in meters. The pathloss of the links involving the IRS is calculated according to [21]. The values of the rest of system parameters are: $K = 5$, $\sigma^2 = -90$ dBm, $\zeta = -30$ dBm, $\gamma_{th+} = 8$ dB, $\eta = 0.7$.

For the DNN training, the size of the data set is 1.5×10^4 which split into training and validation data in the ratio of 80:20. The initial learning rate is 0.001, which decays by a factor of 0.2 after a fixed number of epochs. The mini-batch size is 32, the L2 regularisation parameter is 0.0005 and the validation patience is 10. The training is performed on a Nvidia V100 GPU. After training *BIRS-Net*, it is tested on an unseen test data set of size 10,000. The effective SNR of the backscatter link at the reader is chosen as a metric to evaluate our proposed DNN. For comparison, we adopt the closed form optimal solution for IRS phase shifts from [19] (which requires CSI knowledge) and the optimal α found by exhaustive search as a benchmark.

Fig. 2 shows the training performance of *BIRS-Net* in terms of the loss function of the DNN for an IRS of size $N = 16$. The loss function takes on very large values in the beginning, due to random weights assigned to the network at the start of the training. However, as the training progresses, the network learns the underlying pattern of the training data, and therefore, with ample training iterations, a smaller error margin between the curves is achieved.

Fig. 3 plots the effective SNR of the combined direct and via IRS link traversed by the backscatter signal to arrive at the reader, as function of the IRS size. It can be seen that the increase in IRS size improves the SNR at the reader, which is intuitive since a larger IRS enhances the effective gain of the reflecting path. Moreover, the rate of increase in SNR with the increase in N slightly levels off as N increases. It is also noteworthy that the benchmark optimal solution is obtained with full CSI knowledge, whereas our proposed solution is under the assumption of no CSI. Therefore, despite the gap between the two plots, the performance of our proposed scheme is surprisingly good.

Fig. 4 illustrates the impact of the IRS size on the tag splitting ratio. It is seen that with the increase in IRS size the optimal value of the tag splitting ratio increases. This is due to the fact that with a larger IRS, the signal arriving at the tag is stronger. Therefore, even after harvesting the amount of energy required to power the tag, a significant fraction can be backscattered towards the reader, leading to a higher value of α and a higher SNR.

6. CONCLUSION

In this work, an IRS assisted monostatic BackCom system was studied. To avoid the complex CSI acquisition and the subsequent design of optimal passive beamforming, a DL based framework was proposed to learn the IRS configuration and power splitting ratio at the tag to maximise the effective SNR of backscatter transmission. This involved the implementation and training of a DNN, that achieved direct mapping of the received pilots to desired IRS phase shifts and tag splitting ratio without explicitly estimating the channels. Simulation results showed near optimal performance of the proposed DNN based framework.

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