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Wideband Channel Estimation with Imperfect Hardware for Reconfigurable Intelligent Surfaces

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Abstract

Channel estimation is central part of reconfigurable intelligent surface (RIS) aided communication for active and passive beamforming. The primary challenge behind channel estimate is large dimensionality stemming from not only massive number of RIS elements but also many antennas in base station. Large dimensionality leads to excessive usage of pilot tones for OFDM signals implying high overhead and decreased throughput. To alleviate the high usage of pilots for channel estimation, in this study we propose to have a low complexity transmitter at the RIS simplifed with an aggressive clipping policy and a robust channel estimator against clipping. For robust channel estimation, a generative machine learning model is adapted to exploit prior information to compensate the information loss due to clipping. The simulation results clearly indicate that the proposed estimator has quite a large resiliency for clipped transmitted signals as compared to linear channel estimators.

Keywords: Channel estimation, Reconfigurable intelligent surface, Machine learning, Clipping

İdeal Olmayan Donanıma Sahip Yeniden Yapılandırılabilir Akıllı Yüzeyler için Geniş Bant Kanal Kestirimi

Öz

Kanal kestirimi, aktif ve pasif huzme oluşturma amaçlı kullanılan yeniden yapılandırılabilir akıllı yüzeyler (RIS) destekli iletişimin merkezi bir parçasıdır. Kanal kestiriminin arkasındaki temel zorluk, çok fazla RIS öğelerinden ve aynı zamanda baz istasyonundaki birçok antenden kaynaklanan büyük boyutluluktur. Büyük boyutluluk, OFDM sinyalleri için pilot tonların aşırı kullanımına yol açar, bu da fazla ek yük ve azalan veri hızı anlamına gelir. Kanal kestiriminde pilotların fazla kullanımını azaltmak için bu çalışmada, RIS'de düşük karmaşıklığa sahip bir vericiye sahip olmak için agresif bir kırpma politikası ve kırpmaya karşı dayanıklı bir kanal kestirimi öneriyoruz. Dayanıklı kanal tahmini için, kırpmadan kaynaklanan bilgi kaybını telafi etmek üzere önceki bilgileri kullanan üretken bir makine öğrenimi modeli uyarlanmaktadır. Simülasyon sonuçları, önerilen kanal kestiriminin, doğrusal kanal kestirimleri ile karşılaştırıldığında kırpılmış iletilen sinyaller için oldukça büyük bir esnekliğe sahip olduğunu açıkça göstermektedir.

Anahtar Kelimeler: Kanal kestirimi, Yeniden yapılandırılabilir akıllı yüzeyler, Makine öğrenimi, Kırpma

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1. INTRODUCTION

Optimizing propagation environments via deploying reconfigurable intelligent surface (RIS) on various objects have spurred great interest for achieving diverse communication objectives, including coverage, capacity and energy efficiency [1]. RIS can be viewed as a planar array, implemented either with reflect arrays [2] or metamaterials [3], consisting of many nearly-passive discrete elements. By adjusting the amplitude and phase of these elements according to wireless channels in real-time, the incident signals on RIS are constructively reflected to be aligned with the main data streams between a base station and users while eliminating interference by destructively reflecting signals to non-intended receivers. This reflection based passive beamforming obviously enhances the received signal power at the expense of increased pilot overhead due to the need for channel state information (CSI) between RIS and a base station as well as RIS and users.

The existing approaches to acquire CSI have centered on estimating cascaded user-RIS-base station channel, i.e., the end-to-end channel from a user to a base station through a RIS at the base station with a least-squares (LS) estimator [4-6], minimum mean square error (MMSE) estimator [7], and compressed-sensing algorithms [8,9]. Although estimating the concatenated end-to-end channels is usually sufficient to obtain the beamformers [5], this leads to lengthy pilot sequences mainly because of the large dimensional channel between base station and RIS. Furthermore, many papers model the overall RIS as completely passive. As opposed to these, RIS is designed nearly-passive [1], meaning that although RIS elements do not have a dedicated transmitter and receiver, there can be a separate low complexity transmitter and receiver module to communicate with a central station to periodically obtain the appropriate amplitude and phase shift values of each element.

The main contribution of this paper is to design a channel estimator if there exists a low-complexity transmitter in the RIS. Our approach is quite different than [10], which suggests to employ a number of receivers for some RIS elements. Our motivation behind having a transmitter instead of a receiver at the RIS side is to communicate one pilot symbol per transmitter irrespective of the number of base station antennas and move the signal processing complexity out of RIS. Once the channel matrix between a base station and RIS is estimated, the other channels can be estimated relatively easily with a few pilots.

In this work, we first propose a low-complexity transmitter model with imperfect hardware that is placed in the RIS. Then, we develop a hardware-aware channel estimator motivated by the fact that the performance of LS and MMSE estimators detoriates quite a lot at low complexity hardware [11-12]. Lastly, we show the energy efficiency of our proposed approach and provide the related simulation results.

2. SYSTEM MODEL

In an RIS-aided communication system, a base station can accommodate multiple users by ensuring a certain data rate to each user if the elements of the RIS are optimized properly to constructively reflect the main data streams in addition to the beamformers in the base station. We assume that a base station equipped with M antenna elements communicates with U single antenna users via an RIS with N elements over K subcarriers where $U \ll M \ll N$.

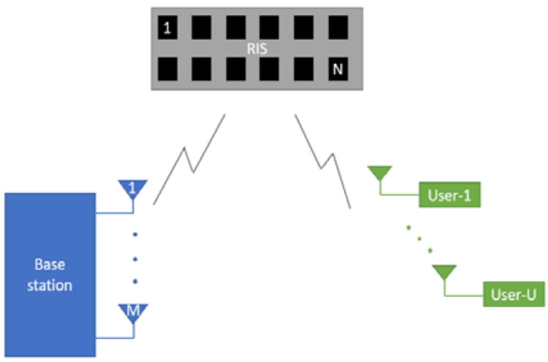

Figure 1. The system model that has a base station with M antennas, U number of single-antenna users and an RIS with N elements.

To estimate the uplink channel in Figure 1, e.g., the channel from a user to the base station, the received signal in the frequency domain for the k[th] subcarrier can be expressed as

$$R_k = (D_k + H_k \Theta G_k) Y_k^{1/2} X_k + V_k \quad (1)$$

where D_k is the MxU matrix due to the direct channel between all the users and the base station, H_k is the MxN channel matrix between the RIS and the base station, and G_k is the NxU channel matrix between the RIS and all the users. Further, Y_k is a UxU diagonal matrix, whose diagonals represent the transmitted power at the k[th] subcarrier for the u[th] user, and X_k is the $Ux1$ transmitted signal vector. The zero mean Gaussian noise vector is denoted as V_k with variance σ_n^2.

Each RIS element is decomposed as

$$\theta_n = \beta_n \exp(j\phi_n) \quad (2)$$

where ϕ_n denotes the phase shift value selected from a finite set and $\beta_n \epsilon [0,1]$ is the attenuation. This constitutes the diagonal matrix

$$\Theta = \begin{pmatrix} \theta_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \theta_N \end{pmatrix} \quad (3)$$

to adjust the amplitude and phase of each RIS element in equation (1). The fundamental challenge to optimize the matrix Θ in equation (1) lies in estimating the channels D_k, H_k, G_k. Notice that this leads to sending at least $N+1$ pilot vector per coherence time with the classical LS or LMMSE estimators [4], [7]. Such a pilot overhead dramatically decreases data rate and hence energy efficiency since $N \gg 1$, and can even override the benefits of deploying an RIS to support the weaker links.

Optimizing the matrix Θ requires channel estimation. In this study, we focus on estimating H_k for $k = 1, \ldots, K$ with reasonable number of pilots. This is challenging due to large dimensionality. Our methodology to tackle this problem is as follows:

- Employ a low-complexity transmit RF chain at the RIS side, and
- Send a single pilot tone per coherence bandwidth from this transmitter.

Since it is not plausible to have a sophisticated transmitter at the RIS, we need simple transmit architecture and hence developing a robust channel estimator against hardware impediments is mandotory to estimate the channel between an element of the RIS and the BS, i.e., n[th] column of H_k which is a $Mx1$ vector denoted by $H_{k,n}$.

Note that after estimation of $H_{k,n}$ the entire channel matrix H_k can be found in many different ways without sending any pilots from the other RIS elements. One typical appoach is to make use of compressed sensing [10]. Additionally, a few transmit RF chains can be utilized instead of a single transmit RF to make a compromise between finding the missing entires of the channel more accurately versus having slighty more hardware cost at the RIS. It is trivial to adapt all the proposed ideas in case of there is a few transmit RF chains. Optimizing this number and finding more efficient methods than compressed sensing are interesting problems for future research.

The main advantage of having a transmit RF chain instead of a receive RF chain at the RIS is to carry over the computational complexity of signal processing for channel estimation to base station. Although one may argue that channel can be estimated with the help of a server communicated with an RIS, the delay due to message exhange between an RIS and server may not be tolerable for channel estimation. Also our approach avoids feedback overhead for base station beamforming.

3. HARDWARE TOLERANT CHANNEL ESTIMATOR

Employing a full-fledged transmit RF chain can be too costly for the RIS. Thus, we first propose a simplified transmitter model. Then, we develop a hardware tolerant estimator to make a reliable channel estimation despite the simplified transmitter, and show the energy efficiency.

3.1. A Low Complexity Transmitter Model

The main complexity of a transmitter comes from digital-to-analog converters (DACs) and power amplifiers. To alleviate the complexity of these elements, clipping can be employed. Clipping essentially limits the signal to lie above or below a predetermined threshold at the expense of bringing nonlinear distortion. If the signal is considerably clipped, it is possible to devise low complexity DACs and power amplifiers. Grounded with this idea, we investigate the impacts of transmitting clipped signals on channel estimation for the RIS.

In order to better perceive how clipping can simplify DACs, the clipping threshold $\mp\Gamma_{\text{thr}}$ can be associated with quantization yielding

$$\Delta_q = \frac{2 * \Gamma_{\text{thr}}}{2^n - 1} \tag{4}$$

where n is the the DAC resolution in number of bits and the average quantization noise power for a uniform quantization distribution between $-\Delta_q/2$ and $\Delta_q/2$ is ${\Delta_q}^2/12$. From equation (4), one can infer that that decreasing the clipping threshold enables us to reduce the DAC resolution without increasing the quantization noise, e.g., decreasing Γ_{thr} 8-fold means approximately 4-bit less quantization resolution since the threshold is multiplied by 2.

Another serious challenge in designing a simple transmitter is large peak-to-average power ratio (PAPR) for OFDM signals, causing an expensive linear power amplifier with large back-off. With a high PAPR only a large back-off can ensure to operate in the linear regime of the power amplifier to avoid signal distortion and out-of-band emission [13]. On the other hand, a large clipping greatly decreases the PAPR of the signals, and this results in utilizing a cheap nonlinear power amplifier similar to the ones used in constant-envelope modulations [14]. Furthermore, clipping facilitates the design of an automatic gain controller (AGC), which aims to balance the quantization and clipping distortion.

Keeping all these in mind with an aggressive clipping, it is possible to design a low-complexity transmitter regarding the DAC and power amplifier for the RIS. To measure the level of clipping, as a performance indicator we define

$$\Gamma_{\text{clip}} = \frac{\Gamma_{\text{thr}}}{\sigma_{ris}} \tag{5}$$

where

$$\sigma_{ris}^2 = \sum_{k=1}^{K} \psi_k \tag{6}$$

and ψ_k is the power of OFDM signal at the k$^{\text{th}}$ subcarrier at the RIS before clipping.

Eventually, clipping encapsulates and dominates many transmitter impairments. Thus, defining Γ_{clip} works as a proxy for low complexity hardware design. However, clipping is a nonlinear operation and yields out-of-band emissions that aliases with the in-band signal in case of Nyquist sampling rate. Because of this, the linear channel estimators in OFDM such as least-squares (LS) and linear minimum mean square error (LMMSE) perform very poorly as illustrated in Section 4. We now propose a robust channel estimator against clipping.

3.2. Channel Estimation

The main problem for this part is to estimate the channel between the RIS and the base station presented in Figure 1. More mathematically, the goal is to estimate H_k for $k = 1, \dots, K$. To this end, pilot symbols on frequency domain are utilized as $P = [P_1, \dots, P_K]^T$ over subcarriers to estimate the channel between an RIS element and the base station by assuming without any loss of generality that coherent bandwidth is at subcarrier level. Modulating the K-dimensional pilot vector P with the KxK inverse discrete Fourier transform (IDFT) matrix F^H and clipping results in such a transmitted signal

$$S = C_{dist} \circ F^H P \tag{7}$$

where C_{dist} is the distortion operator and $\circ$ denotes the Hadamard product. Notice that $S = [S_1, \dots, S_K]^T$

such that S_k is the signal transmitted from RIS at the k[th] subcarrier, whereas X_k in equation (1) is the transmitted signal from the users at the k[th] subcarrier.

OFDM signals are composed of real and imaginary parts, therefore clipping can be applied separately to the quadrature and in-phase components given by

$$\begin{aligned}&[C_{dist} \circ F^H P\,]_k \\ &= \ Re([\,F^H P]_k)\,\intercal_{[-\Gamma_{\mathrm{thr}} \leq Re(F^H P\,)]_k \leq \Gamma_{\mathrm{thr}}]} \\ &+ \ Im([\,F^H P]_k)\,\intercal_{[-\Gamma_{\mathrm{thr}} \leq Im(F^H P)\,]_k \leq \Gamma_{\mathrm{thr}}]}\end{aligned} \tag{8}$$

where $\intercal$ is the function such that it is 1 if the condition is ensured; otherwise it sets the related component to either Γ_{thr} or $-\Gamma_{\mathrm{thr}}$. Re and Im are the real and imaginary part of the signal in the time domain.

Transmitting the clipped signal followed by discrete Fourier transform (DFT) produces the received signal in the frequency domain at the m[th] antenna of the base station as

$$Y_m = \sqrt{\rho} F H_m S + Z_m \tag{9}$$

where Y_m is a $Kx1$ vector, i.e., the m[th] column of the KxM matrix $Y = [Y_1, \dots, Y_M\,]$, $\sqrt{\rho}$ is the received signal-to-noise-ratio (SNR), H_m is the KxK channel matrix between the active element of the RIS and the m[th] base station antenna, and Z_m is additive white Gaussian noise (AWGN) defined as the m[th] column of the KxM matrix $Z = [Z_1, \dots, Z_M\,]$.

The main goal of this part is to estimate the channel H_m from the observations Y_m in (9) for $m = 1, \dots, M$ by using a single pilot vector. This is challenging because of the clipped pilot signals that lead to inter-carrier interference and SNR degradation. To compensate these losses, we use an estimator that exploits prior knowledge from the channel either by using a measured dataset or by using the generated samples from a statistically known channel, and injects this knowledge to the associated channel estimator. In this respect, we make use of the recently proposed GAN-based channel estimator [15,16].

Our main differences from these works are as follows: (i) the goal of [15] and [16] is to reduce the number of pilots for the narrowband and wideband channels respectively, whereas our goal is to cope with the clipping distortion; (ii) [15] and [16] do not consider RIS aided communication. Furthermore, the statistics of the wideband channel between the two static nodes, i.e., the RIS and the base station changes very slowly and this avoids frequent training of the GAN. More precisely, for our case only the number and location of the scatterers can affect the channel, and as shown in [16] these changes do not require retraining of the GAN. This means that a machine learning based channel estimator with a training process seems quite appropriate to estimate the channel between the RIS and the base station.

To adapt the GAN-based channel estimation, we formulate (9)

$$Y_m = \sqrt{\rho}[S^T \otimes F\,]\underline{H}_m + Z_m \tag{10}$$

where $\otimes$ is the Kronecker product, and $\underline{H}_m$ is the vectorized channel acquired by concatenating the columns. Then, we formulate the problem as

$$z^* = \arg\min_z \left\| Y_m - \sqrt{\rho}[S^T \otimes F\,] G(z) \right\|_2^2 \tag{11}$$

where G is the pretrained generator network of the GAN and z is its input. Note that a GAN is composed of two networks, namely a discriminator D and a generator G. Optimizing (11) yields the channel estimate

$$\underline{H}_m = G(z^*) \tag{12}$$

The simple block diagram of the channel estimator relying on equation (11) and (12) is provided in Figure 2 for completeness. In this framework, the generator and discriminator networks are first trained and then the generator is utilized for channel estimation.

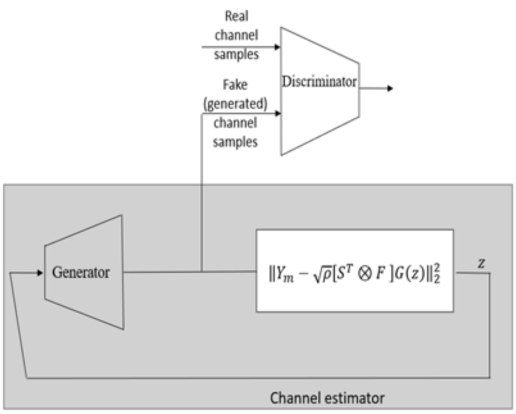

Figure 2. Proposed estimator.

It is worth noting that this method can also be trivially adapted to estimate the channels between user and RIS as well as the channels between the user and base station. Alternatively, simple LS estimator can also be used for these uplink channels with a few pilots due to the single antenna users.

3.3. Energy Efficiency

In this part, the effect of having a low-complexity transmit RF chain in the RIS is studied in terms of energy efficiency, which is defined as

$$\mu_{EE} = \frac{spectral\ efficiency\ (\mu_{SE})}{total\ power\ consumption} \tag{13}$$

Employing a single or a few transmit RF chain increases the total power consumption of the RIS. This, however, improves the energy efficiency of the link due to the decreased number of pilots as compared to the conventional approach of having no transmitter and receiver in the RIS and estimating the cascaded channel by sending a single pilot for each RIS element.

For uplink channel estimation, the conventional method utilizes $N+1$ pilots for each user, namely N pilots for the indirect channel between RIS and base station, 1 pilot for the direct channel between a user and base station. To balance the channel estimation quality with the burden of sending pilots, it is generally a good choice to use the half of the coherent time for pilots and the other half is for data transmission [17]. With all these, according to the equation (1) the energy efficiency becomes

$$\mu_{EE} = \frac{\frac{1}{2}\sum_{k,u=1}^{K,U} \log_2\left(1 + \frac{\frac{P_k}{U}||(\mathbf{D}_{k,u} + \mathbf{H}_k\Theta\mathbf{G}_{k,u}||_2^2}{\frac{P_k}{U}\sum_{j\neq u}||(\mathbf{D}_{k,j} + \mathbf{H}_k\Theta\mathbf{G}_{k,j}||_2^2 + \sigma_n^2}\right)}{P_t + P_{BS} + P_{UE} + P_{RIS}} \tag{14}$$

where $D_{k,u}, G_{k,u}$ are the uth column of the associated D_k, G_k matrices, and the total transmission power is

$$P_t = \sum_{k=1}^{K} ||Y_k E[X_k^H X_k]||_2^2 \tag{15}$$

Additionally, P_{BS}, P_{UE}, P_{RIS} represent the power consumed by the base station, user, and RIS, respectively.

In our proposed scheme N_{xmit} number of low-power transmit RF chains are utilized at the RIS essentially for channel estimation purpose. This brings additional power consumption at the RIS shown by P_{xmit}. On the other hand, this can decrease the number of pilots from $N+1$ to $N_{xmit}+1$ with the proposed estimator. Hence, the energy efficieny in equation (14) scales with

$$\mu_{EE}^{(proposed)} = \frac{N+1}{N_{\text{xmit}}+1}\frac{P_{\text{tot}}}{P_{\text{tot}} + P_{\text{xmit}}}\mu_{EE} \tag{16}$$

where

$$P_{tot} = P_t + P_{BS} + P_{UE} + P_{RIS} \tag{17}$$

Since P_{xmit} consumes substantially low power with respect to P_{tot}, when $N \gg N_{xmit}$, it is apparent from equation (16) that

$$\mu_{EE}^{(proped)} > \mu_{EE} \tag{18}$$

4. NUMERICAL RESULTS

4.1. Simulation Settings

The considered system composed of a base station, RIS and users shown in Figure 1 communicates via OFDM waveform over a TDL channel model similar to [16]. The relevant communication parameters utilized for our simulations are given in Table 1.

Table 1. Simulation parameters

Parameters	Values
Number of subcarriers, K	64
Subcarrier spacing	15 kHz
Bandwidth	20 MHz
Number of users, U	16
Number of base station antennas, M	64
Base station antenna type	Uniform rectangular array
Antenna spacing	$\lambda/_2$
Maximum doppler shift	5Hz
Delay spread	100ns
Delay profile	TDL-E

For the proposed channel estimator in Figure 2, we train a Wasserstein GAN [18,19] with DCGAN architecture [20]. Then, the discriminator network D is discarded and the generative part G is utilized as explained in Section 3.2. The GAN parameters for training are illustrated in Table 2.

Table 2. GAN training parameters

Parameters	Values
Number of training samples	5000
Optimizer	RMSprop
Learning rate	0.00005
Epochs	3000
Batch size	200
Latent dimension	15

4.2. Comparisons

The proposed estimator is compared with the linear LS and MMSE estimators that are commonly utilized for many sorts of applications. The estimation quality is measured in terms of normalized mean squre error (NMSE) defined for the mth antenna as

$$NMSE, m = E\left[\frac{||\underline{H}_m - \widehat{\underline{H}_m}||_2^2}{||\underline{H}_m||_2^2}\right] \quad (19)$$

Notice that averaging (19) over receive antennas yields NMSE. To implement a simplified transmitter model at the RIS, clipping is considered with different levels in terms of Γ_{clip} as stated in equation (5).

In Figure 3, the transmitted signal is clipped by setting the clipping threshold to 1/4 of the standard deviation of the transmitted signal, Although LS and LMMSE estimators are greatly impacted from this amount of clipping as compared to unclipping, our proposed GAN based estimator shows quite robust performance as can be observed in Figure 3.

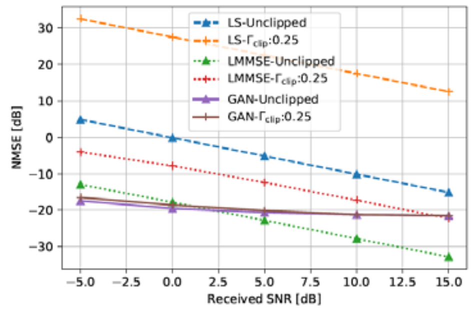

Figure 3. The performance comparison of the proposed method with respect to the LS and LMMSE estimators

Next the performance of the proposed estimator is plotted for various clipping ratios for 2 different received SNRs at 5dB and -5dB. Promisingly, our estimator does not degrade much even if too agreessive clipping exists at the transmitter as depicted in Figure 4, where

$$\text{Clipping Ratio} = 10\log_{10}(\Gamma_{clip})^2. \quad (20)$$

Note that in Figure 4, Γ_{clip} and hence Γ_{thr} in equation (5) are variables. This verifies that having a very low complexity transmitter at the RIS does not decrease the channel estimation performance at the base station for our estimator.

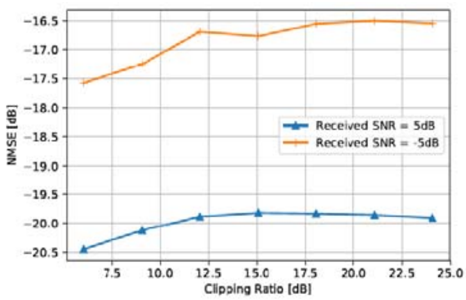

Figure 4. The performance of the proposed estimator with respect to different clipping ratios.

5. CONCLUSION

In this study, RIS aided communication is considered for channel estimation problem. We argue that the primary challenge of high dimensional estimation leading to many pilot symbols is tackled with an estimator that works well with clipped transmitted signals relying on a GAN based estimator that can leverage the channel structures in the training phase and use it as prior information to compensate the information los due to clipping. The effectiveness of the proposed approach is clearly presented via simulation results.

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