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Research paper

Robust Channel Estimation and Passive Beamforming with Discrete Phase for RIS-Assisted Communication Systems

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Abstract

Background and Objectives: This research addresses the issue of channel estimation and beamforming in systems with Reconfigurable Intelligent Surface (RIS). RIS can significantly improve coverage by controlling the phase and amplitude of the reflected signals through nearly passive elements. This advantage is highly dependent on the availability of accurate channel state information (CSI), which is difficult to obtain, and even more so in realistic scenarios where the RIS phase variations are limited to a small number of discrete surfaces due to hardware limitations.
Methods: To study this issue, we propose a new CSI estimation paradigm called recursive averaging, which extends the traditional least squares (LS) estimator but compensates for its weaknesses under low SNR and quantized phase regimes, known as RALS. The new approach involves combining a recursive update scheme that sequentially improves the CSI estimates through recursive averaging and an adaptive feedback framework. This provides better robustness against noise and quantization-induced distortion, and allows for more precise RIS configuration under the hardware constraints of a non-ideal system. The aim is to reduce the channel estimation error and reduce the bit error rate (BER) by considering the practical implementation of the method. In addition, this study also investigates the effect of the discrete phase.
Results: We analyze the performance of RALS under idealized continuous-phase and discrete-phase scenarios, where the phase of each RIS element is quantized with a finite number of bits. Simulation results show that RALS outperforms traditional LS and other reference estimators measured in MSD and BER, especially in situations where the number of quantized bits is low or the SNR is poor.
Conclusion: Simulation results show that the proposed method provides higher accuracy channel estimation with less estimation error. Integrating accurate channel estimation with an efficient beamforming strategy, overall system performance is significantly enhanced. More specifically, it is shown through simulations that 4-bit resolution is sufficient for phase discretization considering real reflection phase constraints. Interestingly, the devised approach achieves such improved performance without engaging in huge computational complexity, thus being feasible to implement in real-time in RIS-based systems.

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Introduction

Improvement of communication service quality is the top priority of sixth-generation (6G) wireless networks. As the adoption of mobile devices has been increasingly rapid, data transmission efficiently has become unavoidable. For this reason, improvements in bandwidth, system capacity, reliability, and Quality of Service (QoS) need to be studied [1]. In addition, the mm-Wave/sub-THz bands are under rapid examination in recent research efforts. As these bands have a tendency to be affected by physical obstacles and propagation attenuation, however, they have the potential to provide enormous improvement in 6G communication system performance. To compensate for these disadvantages, RIS technology has recently been put forward [2].

An RIS has the capability of configuring the wireless propagation environment through the dynamic manipulation of incident signals. This permits manipulation of the wireless medium, such as destructive reflection, inhibiting eavesdropping by unwanted users [1].

In addition, because RIS consists of many passive reflecting elements that are low-power and inexpensive, it requires much less power when compared to traditional relays and MIMO antennas [3]-[5]. The phase of each reflective element can be changed in real-time through an intelligent controller, and hence allows favorable wireless channel properties [6]. As a result of these benefits, in conjunction with simplicity of deployment and technology compatibility such as MIMO, RIS has attracted vast research interest in domains including channel modeling and estimation, beamforming design, hardware impairments, and wireless power transfer. Inclusion of RIS in wireless networks has the potential of enhancing coverage, enhancing data rates, and network security [7]-[10].

Channel estimation is an important challenge in RIS-aided networks due to its direct impact on beamforming and service quality. Accurate CSI of RIS-aided channels is needed to implement the signal processing techniques, such as beamforming at the base station and RIS. However, if RIS elements are strictly passive and lack embedded sensors, then direct measurement of the user-RIS and base station-RIS channels is impractical. In most previous studies, an assumption has been made that the complete CSI of the channels is provided at the receiver end [11]-[13]. Various approaches and methods have been proposed to estimate RIS-aided channels effectively. In one such approach, RIS elements are turned on and off successively such that only a single RIS element is active per time slot, so an interference-free estimate of the reflected channel may be obtained. The number of used time slots tends to be proportional to the number of RIS elements [14], which may be time-consuming in practice.

Another approach utilizes fully active RIS elements and particular matrices (e.g., Discrete Fourier Transform (DFT) or Hadamard matrices) to make channel estimates [15]. Various estimation methods such as LS [16], Linear Minimum Mean Square Error (LMMSE) [17], Compressive Sensing [18], and Matrix Decomposition have been employed depending on the channel model. Among them, LS has been extensively used due to the simplicity and practicability of actual implementation.

While most previous work on RIS-based systems relies on ideal phase shifts, this assumption is usually far from reality. In reality, the phase shift of each RIS element tends to be limited to a small number of discrete levels due to the limitations of low-precision digital phase adjusters and limited bit quantization. As such, phase quantization leads to a significant loss of beamforming accuracy, especially at low signal-to-noise ratio (SNR) levels [19], [20].

Related Works

In [16], LS combined with the on-off method was utilized to estimate both the direct and RIS-assisted channels.

The authors of [21], investigated an uplink OFDM-powered SISO-RIS system with numerous RIS elements, raising the complexity of estimating channels and designing reflections. Reducing such overhead was proposed by clustering neighboring RIS elements with correlated channels into subpanels with a common reflection coefficient. Pilot signals were used to estimate the direct and cascaded channels through LS by turning on one group of RIS elements at a time. Grouping allows a compromise of training time and computational complexity. Several amendments to LS estimation, especially in multi-user settings, have been introduced.

In [22], another user's reference CSI was used to model other users' channels as scaled low-dimensional representations, so that LS estimation could be efficiently conducted at the base station with largely reduced training overhead. In addition, LS-based and multi-protocol training-channel-estimation approaches were proposed in [23], [24] for dual-RIS-panel systems with the aim of achieving low training costs.

However, the previous works make assumptions of RIS phase shifts being ideal and continuous, which would not hold true in practice. In practical hardware implementations, RIS elements are generally subject to discrete phase shifts because of quantization limitations. This may be introduced as a perceivable performance loss in the task of estimation and beamforming.

In [25], discrete phase shifts were demonstrated to possess constant proportional power loss with respect to ideal continuous phase shifts. In [26], the authors have theoretically proved that at least three levels of quantization must be used to achieve full diversity in RIS-aided configurations. These findings highlight the necessity of creating channel estimating algorithms, which are phase-quantization resilient, to be employed in realistic RIS deployments.

In [27], the effects of reduced phase shifts on the data rate that is attainable were investigated, and the results showed that the loss worsens when the levels of quantization are reduced. In another related work, [28] introduced a low complexity approach to channel estimation and passive beamforming with discrete phase shift constraints and showed that good group-based designs and optimized training sequences are efficient in suppressing quantization-caused degradation.

From previous studies, LS has proven to be straightforward and easily applicable in practice, but LS has poor estimation precision under poor SNR situations. This work aims to enhance the estimation precision via an improved LS-oriented approach, verified by means of the Mean Squared Deviation (MSD) performance metric.

To address this, we propose an enhancement of the LS algorithm for CSI estimation in RIS-assisted systems. Specifically, a recursive averaging LS approach is introduced. This iterative algorithm updates the CSI estimate based on the received signal and current estimate, enabling accurate estimation of the transmitter-RIS-receiver paths, which is critical for designing reflection coefficients. A novel phase-matching strategy is proposed in which the RIS element phase is set to the negative phase of the estimated channel coefficient.

In summary, the proposed LS-based learning algorithm, combined with the innovative design of phase coefficients, offers an efficient and effective solution for improving RIS-based wireless communication systems.

Our method is assessed by Mean Squared Deviation (MSD) and Bit Error Rate (BER) under the metrics of estimation and detection performance, respectively. Simulation results are given under diverse SNR levels and are illustrated by comparisons of traditional LS, Least Mean Squares (LMS), [29] and Stochastic Gradient Descent (SGD) learning [30], [35] approaches, and are shown to have an advantageous performance under practical quantization limitations.

The remainder of this paper is organized as follows. Section 2 outlines the system model and assumptions. Section 3 discusses the LS-based estimation methods, including conventional LS, LMS, and the proposed learning algorithm.

Section 4 presents the RIS phase design strategy tailored to the estimated channels. Section 5 includes numerical simulations and performance comparisons. Finally, Section 6 concludes the paper and summarizes the key contributions.

System Model

In this section, we examine the wireless communication system illustrated in Fig. 1, which consists of a source, a destination, and a Reconfigurable Intelligent Surface (RIS). The RIS is assumed to have N tunable reflecting elements and an intelligent controller capable of adjusting the phase of the incident signal based on the phase information derived from the Channel State Information (CSI).

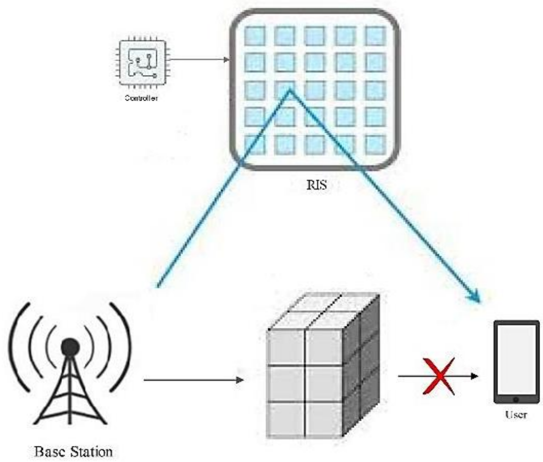

Fig. 1: System model.

The direct line-of-sight (LOS) path between the source and the destination may be obstructed by physical obstacles. However, due to the presence of numerous scatterers in the wireless environment, the propagation between the source and destination is modeled as a Rayleigh fading channel. This direct channel is denoted by h_d, whose elements are assumed to be independent and identically distributed (*i.i.d.*) complex Gaussian random variables with zero mean and unit variance $h_d \sim \mathrm{CN}(0, \mathrm{I})$.

In contrast, the channels between the source and the RIS, as well as between the RIS and the destination, are assumed to follow LoS propagation and are thus modeled as Rician fading channels. Under the Rician fading model, the attenuation coefficients for the source-RIS and RIS-destination links associated with the n_{th} reflecting element (n=1,…, N) are defined as follows:

$$h_n^{SR} = \sqrt{\frac{K_1}{1+K_1}}\bar{h}_n^{SR} + \sqrt{\frac{1}{1+K_1}}\tilde{h}_n^{SR} \quad (1)$$

$$h_n^{RD} = \sqrt{\frac{K_2}{1+K_2}}\bar{h}_n^{RD} + \sqrt{\frac{1}{1+K_2}}\tilde{h}_n^{RD} \quad (2)$$

here, K_1 and K_2 denote the Rician factors for the source-RIS and RIS-destination channels, respectively [31]. The random variables $\bar{h}_n^{SR}$ and $\bar{h}_n^{RD}$ represent the line-of-sight

(LoS) components of the source-RIS and RIS-destination paths, respectively, with the index n corresponding to the n_{th} RIS element. The variables $\tilde{h}_n^{SR}$, and $\tilde{h}_n^{RD}$ represent the non-line-of-sight (NLoS) components, modeled as complex Gaussian random variables with distribution $\mathcal{CN}(0,1)$.

Assuming flat and slow fading conditions, the baseband received signal at the destination can be expressed as:

$$r[i] = (\sum_{n=1}^{N} h_n^{SR} \gamma_n e^{j\varphi_n} h_n^{RD}) s[i] + z[i] \quad (3)$$

where, φ_n denotes the adjustable phase shift introduced by the n_{th} RIS element, γ_n is the reflection amplitude coefficient, which is a real number satisfying (0≤γn≤1), $s[i]$ is the transmitted symbol drawn from an M-PSK constellation with unit power, and $z[i]$ is a sample of additive white Gaussian noise (AWGN) with variance σ_z^2.

The channel fading coefficients can be expressed in polar form as:

$$h_n^{SR} = |h_n^{SR}| e^{j\angle h_n^{SR}} \quad , \quad h_n^{RD} = |h_n^{RD}| e^{j\angle h_n^{RD}} \quad (4)$$

where, $|h_n^{RD}|$ and $|h_n^{SR}|$ represent the magnitudes, and $\angle h_n^{SR}$ and h_n^{RD} represent the phases of the respective channel coefficients. Thus, the received signal can be rewritten as:

$$r[i] = \left(\sum_{n=1}^{N} |h_n^{RD}||h_n^{SR}| \, \gamma_n e^{j(\varphi_n + \angle h_n^{SR} + h_n^{RD})}\right) s[i] + z[i]. \quad (5)$$

By configuring each RIS element's reflection coefficient optimally:

$$\varphi_n = -\angle h_n^{SR} - \angle h_n^{RD} \quad , \quad \gamma_n = 1 \quad (6)$$

The received signal simplifies to:

$$r[i] = \underbrace{(\sum_{n=1}^{N} |h_n^{RD}||h_n^{SR}| \;)}_{K} s[i] + z[i] \quad (7)$$

From this expression, the Signal-to-Noise Ratio (SNR) at the receiver is derived as:

$$SNR = \frac{K^2}{\sigma_z^2} \quad (8)$$

Assuming a large number of RIS elements N, the received SNR increases correspondingly. Thus, increasing the number of RIS elements can significantly improve the overall detection performance in wireless systems. However, this enhancement is highly dependent on accurate channel estimation. It is crucial to note that if the channel estimation and reflection coefficient configuration are not performed precisely, the performance of the wireless system will not improve. Given the importance of these two processes, Section 3 describes adaptive channel estimation methods, and Section 4 outlines the procedure for configuring RIS reflection coefficients.

Channel Estimation

To address the channel estimation problem in RIS-assisted wireless systems, we consider a scenario where the receiver captures a data stream structured as shown in Fig. 2.

The data stream is divided into frames, each consisting of a header and a data section (Dataℓ). Channel estimation at the receiver is carried out during the reception of the header sections using an on/off switching strategy.

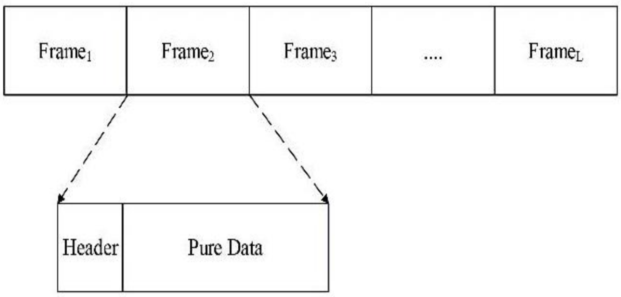

Fig. 2: Data frame structure.

On–Off Estimation Method

Method Steps:

In the first step, all RIS elements are turned off except the first one [14]. Accordingly, the gain and phase of the RIS elements are configured as follows:

$$\gamma_1 = 1, \quad (9)$$

$$\gamma_n = 0, \qquad n = 2,3,\ldots,N, \quad (10)$$

$$\varphi_n = 0, \qquad n = 1,2,\ldots,N. \quad (11)$$

With this configuration, the received signal becomes:

$$r[i] = \underbrace{h_1^{SR} h_1^{RD}}_{w_1^o} s[i] + z[i] \quad (12)$$

where w_1^o represents the effective cascaded channel when only the first RIS element is active. In the next step, all RIS elements are turned off except the second one:

$$\gamma_2 = 1, \quad (13)$$

$$\gamma_n = 0, \quad \forall \; n \neq 2 \quad (14)$$

$$\varphi_n = 0, \qquad n = 1,2,\ldots,N. \quad (15)$$

With this configuration, the received signal becomes:

$$r[i] = \underbrace{h_2^{SR} h_2^{RD}}_{w_2^o} s[i] + z[i] \quad (16)$$

This process is repeated sequentially for all N RIS elements to estimate all cascaded channels. Thus, upon receiving the ℓ_{th}frame with only the ℓ_{th} RIS element active, the corresponding channel $w_\ell^o = h_\ell^{SR} h_\ell^{RD}$ can be estimated.

The power and phase configuration for the ℓ_{th} frame is given by:

$$\gamma_\ell = 1, \tag{17}$$

$$\gamma_n = 0, \qquad n = 3, \ldots, N, \quad n \neq \ell \tag{18}$$

$$\varphi_n = 0, \qquad n = 1,2, \ldots, N. \tag{19}$$

However, most studies in the field of RIS have assumed the existence of continuous phase shifts, while it is challenging to implement such phase shifts in practical systems. It is worth noting that the exact configuration of the reflection phases is impossible, and also, the number of bits allocated for this purpose is limited [25]. To take this into account, we consider a practical setting in which the phase shift in each RIS element can only take a limited number of discrete values, which are assumed to be evenly spaced in the interval [-π,π). We denote the number of bits used to represent each level by *b*. Then the set of phase shifts in each element will be as follows [32]:

$$\mathcal{F} = \{\, 0, \Delta\theta, \ldots, \Delta\theta(\mathrm{U}-1)\} \tag{20}$$

$$\Delta\theta = 2\pi/U, \tag{21}$$

$$\mathrm{U} = 2^{\mathrm{b}}. \tag{22}$$

Moreover, the phase shift of each reflecting element is designed by mapping its optimal value to the nearest point in $\mathcal{F}$.

Least Squares (LS) Estimation Method

The LS method is a fundamental technique widely used for wireless channel estimation due to its simplicity and ease of implementation. However, in RIS-assisted wireless networks, the high number of reflecting elements leads to high-dimensional channels, necessitating improvements to the standard LS approach [33]. Furthermore, LS is commonly used as a mathematical baseline for training deep neural network–based methods, highlighting the importance of its optimization.

The received signal in the ℓ_{th} frame (with on/off RIS structure) used to estimate the ℓ_{th} channel is:

$$r[i] = w_\ell^o s[i] + z[i] \tag{23}$$

The LS algorithm formulates the channel estimation problem as minimizing the following cost function:

$$\widehat{w}_\ell = \arg\min(r - \widehat{w}_\ell\, s)(r - \widehat{w}_\ell s)^H \tag{24}$$

The optimal channel estimate for the ℓ_{th} frame is obtained as:

$$\widehat{w}_\ell = (s^H s)^{-1} s^H r \tag{25}$$

Least Squares Proposed (RA-LS)

We propose a simplified and low-complexity LS-based channel estimation approach, referred to as Recursive Averaging LS (RA-LS), where the instantaneous LS estimates are recursively averaged over multiple observations to improve robustness against noise. In this method, in order to estimate the channel and use the on/off structure, a simple but effective relationship is used to estimate the channel coefficients. It is assumed that at each transmission, only one of the RIS elements is on (active), and the others are off. Therefore, at any given moment, only one specific path is activated through an RIS element and, as a result, the received signal can be directly attributed to the channel of that path. For optimization, a stepwise normalization algorithm is proposed. This algorithm is based on the recursive averaging method which is based on the LS method, this interpolation is done to make the LS method robust against noise. This method can be named as RA-LS (Recursive Averaging LS). If it is assumed that *i* number of pilots are sent (x_i), the received signal will be as follows:

$$y_i = x_i w + n_i \tag{26}$$

In the above Equation, (w) the channel is in the *i-th* transmission. Since only one element is active at any time, initially and in the first step for each received pilot, an initial estimate is determined by the LS method for the algorithm as shown in (27).

$$\widehat{w}_\ell^{(i)} = \frac{y[i]}{x[i]} \tag{27}$$

Then, to strengthen the LS algorithm against noise, interpolation is used as follows [34]:

$$\widehat{w}_\ell^{(i)} = \frac{1}{i}\sum_{k=1}^{i} \frac{y[k]}{x[k]}. \tag{28}$$

Then, in a practical implementation, this estimate is recursively normalized and updated at each stage using (29), and the estimation process is repeated. This equation shows that the new estimate is equal to the previous estimate plus a correction proportional to the current error.

$$\widehat{w}_\ell^{(i)} = \frac{(i-1)\widehat{w}_\ell^{(i-1)} + \frac{y[i]}{x[i]}}{i} \tag{29}$$

$$= \widehat{w}_\ell^{(i-1)} + \frac{1}{i}\left(\frac{y[i]}{x[i]} - \widehat{w}_\ell^{(i-1)}\right) \tag{30}$$

In the above equation, $\left(\frac{y[i]}{x[i]}\right)$ is the instantaneous LS estimate at the *i-th* iteration. In this method, instead of storing and buffering all previous data, the estimate is updated at each iteration using only the previous value and the new value. This method has less computational complexity due to the use of less data and shows better performance in real-time systems. It will also have a simple and efficient implementation.

Least Mean Squares (LMS) Estimation Method

The LMS algorithm is widely used because it does not require the computation of the correlation matrix or its inverse. Instead of minimizing $\mathrm{E}\{e^2\}$, it minimizes the instantaneous squared error e^2 at each iteration [29]. The received signal and error function in the ℓ_{th} frame are similar to those defined in (23) and (24), respectively. The optimization problem for cascaded channel estimation is:

$$w_\ell^o = \min_{w_\ell} f(w_\ell) \quad (31)$$

Using the LMS method, the optimization is solved iteratively. The coefficient update rule is:

$$w_\ell[i+1] = w_\ell[i] - \mu \nabla f(w_\ell[i]) \quad (32)$$

here, μ is the learning rate, and ∇ denotes the gradient. By computing the gradient and substituting it into the update rule, we obtain:

$$w_\ell[i+1] = w_\ell[i] + 2\mu(r[i] - w_\ell s[i])s[i] \quad (33)$$

This update is performed at the receiver to estimate the RIS-assisted channel coefficients between the transmitter and receiver. The stability and convergence condition of the LMS algorithm is defined as:

$$0 < \mu < \frac{1}{3.tr[R]} \quad (34)$$

where tr[R] denotes the trace of the correlation matrix of the received signal.

Computational complexity

This section analyzes the computational complexity associated with the proposed estimation method as follows. In the LMS method, at each iteration, according to (31–33), there are 3N+1 multiplications and 2N+1 additions, resulting in a linear complexity of $O(N)$. In the LS-Traditional method, at each iteration, according to (24–25), due to the need for matrix inversion, the computational cost is $O(N^3)$, which makes this method computationally prohibitive for large-scale RIS. In contrast, the proposed method, as shown in (27–30), achieves a linear complexity of $O(N)$, as summarized in Table 1.

Table 1: the proposed method

Method	Complexity order	Memory
LMS	O(N)	Stores weights
LS-Traditional	$O(N^3)$	Stores full matrix
Proposed	O(N)	Store previous estimate

Design of RIS Reflection Coefficients

After estimating the cascaded channel coefficients $\hat{w}_\ell$ at the receiver, the RIS reflection coefficients can be determined. In our proposed method, the adverse phase effects of the channel are eliminated by configuring the RIS phases to be the negative of the estimated channel phases:

$$\varphi_\ell = -\angle \hat{w}_\ell, \quad (35)$$

$$\gamma_\ell = 1. \forall \ell. \quad (36)$$

The receiver transmits the calculated phase values to the RIS via the intelligent controller. By setting the RIS reflection coefficients accordingly, the received signal becomes:

$$r[i] = \left(\sum_{\ell=1}^{N} |h_\ell^{SR}||h_\ell^{RD}|\right)s[i] + z[i] \quad (37)$$

If the number of RIS elements is sufficiently large, such that:

$$\left(\sum_{\ell=1}^{N} |h_\ell^{SR}||h_\ell^{RD}|\right) > 1. \quad (38)$$

Then, the use of RIS significantly improves the SNR at the receiver, thereby enhancing the overall performance of the wireless communication system.

However, in this work, a more practical case, which considers the discrete phase mode, is also considered and is shown in the simulation section.

Simulations

In this section, we simulate a wireless communication system equipped with a Reconfigurable Intelligent Surface (RIS). To generate the data for the channel estimation problem, we assume that the transmitted symbols are encoded using QPSK modulation. The On/Off method is used to generate pilot signals received at the destination. In the Rician fading model (1), the received signal consists of a strong Line-of-Sight (LoS) component and a weaker scattered component. For this scenario, the Rician factors are set as $K_1 = K_2 = 7$. The Non-Line-of-Sight (NLoS) components of the wireless channel, $\tilde{h}_n^{SR}, \tilde{h}_n^{RD}$, are modeled as complex Gaussian random variables with distribution $\mathcal{CN}(0,1)$. The noise at the receiver is assumed to be Additive White Gaussian Noise (AWGN).

The number of reflecting elements in the RIS is varied from N =1 to N = 16. Assuming perfect Channel State Information (CSI), the detection performance curve is shown in Fig. 3. As illustrated, the overall Bit Error Rate (BER) performance of the wireless system improves with an increasing number of RIS elements. In practical scenarios, however, the receiver does not have access to perfect CSI and must estimate it.

In this study, CSI is estimated using the conventional Least Squares (LS) method [33] and the Least Mean Squares (LMS) method [29]. Channel estimation error using the LS method is significantly higher especially at low SNR compared to LMS.

By employing the LMS channel estimation method based on (31-33), and adjusting the RIS phase shifts according to (35), the BER performance curve is obtained as shown in Fig. 3.

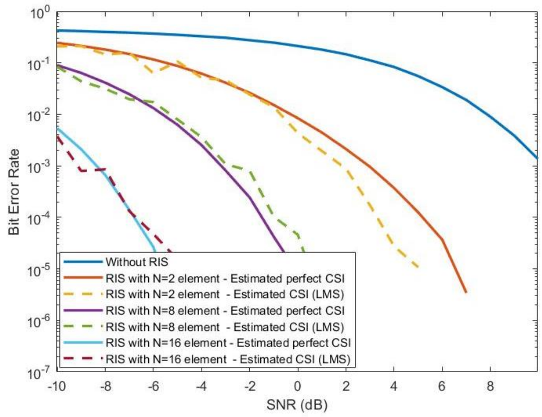

Fig. 3: The BER performance of the wireless communication system assisted by RIS.

The curves corresponding to LMS-based estimation deviate from the ideal channel curve, indicating that LMS is not an ideal estimation method for this scenario.

The learning curves based on the Mean Square Deviation (MSD) are implemented for the LS method (24), the LMS method (31-33), and the proposed method (26-30), under AWGN conditions. The normalized mean square Deviation (NMSD) is used to evaluate the channel estimation performance and is defined as (39):

$$NMSD = \frac{\|h-\hat{h}\|^2}{\|h\|^2} \tag{39}$$

As depicted in Fig. 4, the LMS method outperforms the conventional LS method with significantly lower estimation error. The graph in Fig. 4 demonstrates that as the SNR increases, the NMSEs for all methods improve.

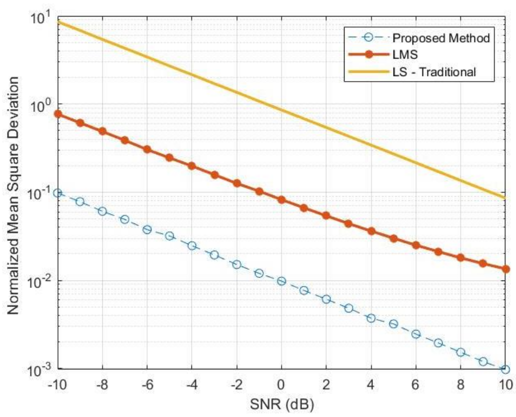

Fig. 4: Average training curve comparison under different SNR levels.

However, our proposed improvement to the LS method achieves even lower estimation error than both, providing a more accurate estimation. Specifically, at SNR= 0dB, it has an average of about 17dB fewer errors than the LS method and an average of about 6db fewer errors than the optimal LMS method.

Subsequently, in Fig. 5, learning curves are plotted for various signal-to-noise ratio (SNR) levels using the LS method, the near-optimal Stochastic Gradient Descent (SGD) method [30], [35], and the proposed method. As evident in the figure, estimation performance improves as the SNR increases. In Fig. 5, it can be seen that in both SNR cases, the error value of the proposed method is lower. In particular, it has a very small error compared to the LS method and has a high convergence speed compared to the optimal SGD method.

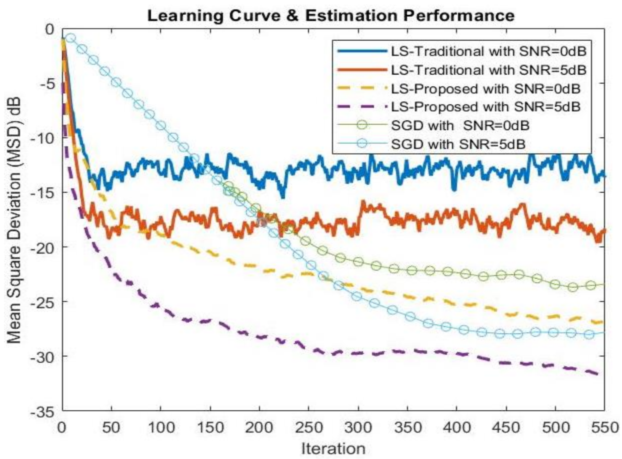

Fig. 5: Learning curve for SGD (learning Rate = 0.01), LS, and the proposed method under different SNRs.

Fig. 6 presents a comparative performance evaluation of the proposed method. The figure clearly shows that the proposed algorithm outperforms LMS in terms of both lower estimation error and improved accuracy. The performance curve of the proposed method closely approximates the ideal curve that assumes perfect CSI availability.

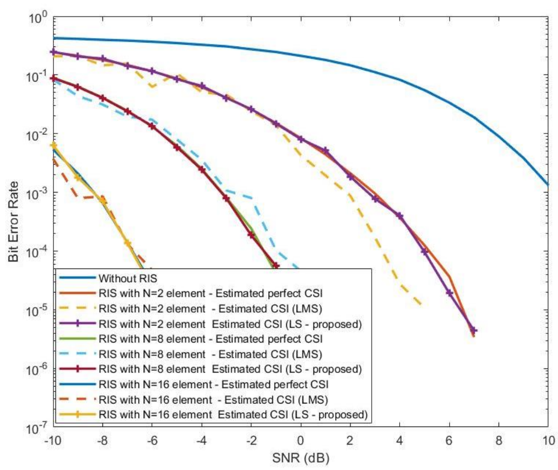

Fig.6: The BER performance of the wireless communication system assisted by RIS

In order to evaluate the impact of practical hardware constraints on the proposed method performance, we incorporate phase quantization into the RIS model. In ideal conditions, RIS elements are assumed to have continuous and perfect phase shift capabilities. However, in realistic scenarios, each RIS element can only implement a finite set of discrete phase values due to hardware limitations.

In our simulation, the estimated continuous phase shifts are quantized to B-bit resolution, meaning that each phase value is selected from (20-22). Specifically, we apply phase quantization after channel estimation by rounding the estimated continuous phase to the nearest available discrete level. This models a practical RIS with low-resolution phase shifters.

In Fig. 7, a study on phase discretization based on (20-22) and for the LMS method has been carried out. According to the discretization performed for 2, 4, and 8 bits, it is observed that the bit error rate for 4 bits and 8 bits for this method are very close to each other and in order to reduce the computational complexity, we will consider phase discretization with 4 bits. At this stage, the reflection coefficient is considered equal to 1. All the graphs show that with phase discretization, BER also decreases with discrete phase, which has now been clarified and BER increases compared to the continuous mode, and the more this discretization is used with a higher number of bits, the closer we will get to the continuous mode. The method utilizing continuous phase shifts outperforms practical phase shifts. This advantage arises from the assumption of no losses in an ideal scenario. However, a compromise must be considered between the number of bits and the time and complexity of calculations.

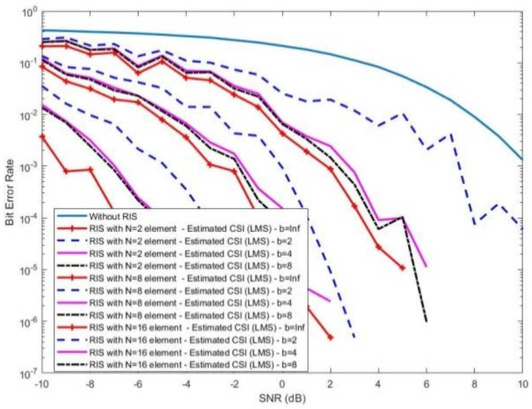

Fig. 7: The BER performance vs SNR, for different values of N and b. (LMS method).

Fig. 8 shows the investigation on phase discretization for the proposed method. According to the discretization done for 4 and 8 bits, it is also observed that the bit error rates for 4 bits and 8 bits for this method are very close to each other and very close to the continuous state. At this stage, the reflection coefficient is considered to be 1. According to Fig. 8, we conclude that the proposed method has shown sufficient robustness to phase discretization. Also, to reduce the complexity, a 4-bit phase can be chosen, which shows an approximately acceptable error value.

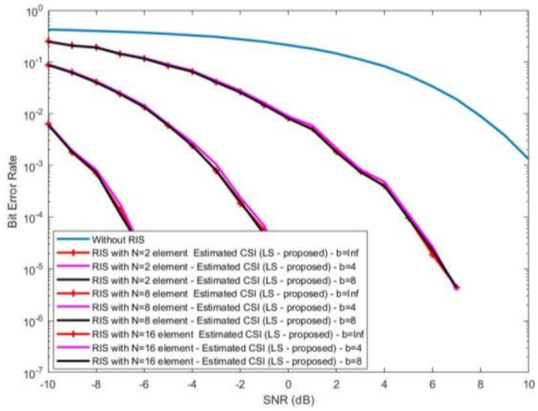

Fig. 8: The BER performance vs SNR, for different values of N and b. (LS Proposed).

Results and Discussion

In this paper, a novel method for channel estimation in RIS-assisted wireless communication systems is presented. As illustrated in Fig. 4, the proposed approach achieves a very low estimation error, demonstrating the high accuracy of the model in reconstructing the channel. Furthermore, as shown in Fig. 5, the proposed method exhibits a fast convergence rate, indicating both the stability and learning efficiency of the algorithm. Table 1 provides a comparison of the computational complexity among various methods. It can be observed that the proposed method maintains a low computational burden while achieving high estimation precision, making it highly suitable for practical hardware implementation. Another notable advantage of the proposed scheme is its robustness against the quantization of RIS phase shifts, as observed in Fig. 8, which ensures stable performance under non-ideal operating conditions. Overall, the results confirm that the proposed method achieves a favorable trade-off between accuracy, convergence rate, and computational cost, while maintaining resilience to practical RIS imperfections. Future studies may extend this framework to multi-user and MIMO scenarios to further evaluate its applicability in realistic 6G wireless environments.

Conclusion

In this work, we introduce an improved channel estimation approach for wireless communication networks with the aid of RIS, which is an extension of the traditional LS method. This improved method adopts an iterative form where the channel estimation uses multiple received symbols and is more robust to noise interference.

Extensive simulation results confirm the efficiency of our approach, showing notably improved estimation quality for a broad range of SNR levels. Our approach is compared with the standard LS and the LMS method and is shown to have generally reduced estimation error and increased stability, even when practical system impairments are taken into account. It also has an acceptable convergence speed.

In addition, we rigorously examined the effect of phase discretization for realizable RIS implementations. Due to the hardware constraints commonly limiting the RIS elements to a finite number of phase shifts, we investigated the effectiveness of the estimation approach under the condition of discretized phases.

Our results verify that 4-bit phase quantization provides a satisfactory hardware complexity vs. estimation effectiveness tradeoff. The decrease in the discrete-phase case is observed to be relatively small in our simulations compared with the optimal case of continuous phases.

In short, the improved LS-based method developed here provides a practical and effective remedy for accurate channel estimation in RIS-assisted networks. It surmounts leading challenges imposed by noise, sparse pilot information, and hardware constraints. The method not only outperforms classical LS and LMS estimators for both continuous-phase and discrete-phase cases, but also is well-suited for the needs of future-generation (6G) wireless networks, wherein extreme reliability, scalability, and implementation feasibility come into importance. This paper lays the groundwork for future studies of adaptive, learning-based, and hardware-aware estimation techniques in intelligent wireless networks.

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Authors' Contributions

Dr. Neda has drawn the general road map. A. Moradband has searched for important papers in this field. Then, with Dr. Neda and Dr. Hajiabadi, the implementation of the proposed method has been carried out. In addition, all authors participated in the analysis of the simulation results and the final editing of the work.

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Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy, have been completely witnessed by the authors.

Abbreviations

RIS	*Reconfigurable Intelligent Surface*
CSI	*channel state information*
LS	*least squares*
LMS	*Least Mean Squares*
SGD	*Stochastic Gradient Descent*
RALS	*Recursive Averaging least squares*
MSD	*Mean Squared Deviation*
BER	*Bit Error Rate*
SNR	*signal-to-noise ratio*
LOS	*Line of Sight*
AWGN	*Additive White Gaussian Noise*

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