A Survey Channel Estimation for Intelligent Reflecting Surface (IRS)

Jiwayria M. S. D. Babiker and Xinlin Huang(✉)

School of Electronics and Information Engineering, Tongji University,
Shanghai, China
{2090007,xlhuang}@tongji.edu.cn

Abstract. An intelligent reflecting surface (IRS), is a new era of wireless communication towards intelligent and reconfigurable wireless networks. IRS can enhance communication quality between the network terminals with a small cost, low complexity, and low energy consumption when the direct connection has been blocked. To obtain the IRS features, the acquisition of channel state information (CSI) is substantial but it's challenging in practice, due to the massive number of IRS elements without any capabilities of signal processing. To deal with this challenge in this survey, we first introduce an overview of channel estimation for IRS, then we address the main recent techniques proposed to estimate channels in IRS with various strategies in different applications. Furthermore, we summarize these recent works and list the main points that affect the estimation of the channel in IRS-aided communication system, and finally outline some future researches in IRS channel estimation and the conclusion of this survey.

Keywords: Intelligent reflecting surface (IRS) · Channel estimation · Pilot symbols

1 Introduction

IRS is a paradigm shift of wireless communications from traditional networks "just active components" to the hybrid networks "active and passive components". This hybrid network will be the backbone of the new technologies like beyond-5G, 6G, and so on.

In wireless communications, an IRS is used to assist the communication between the network terminals when the direct link is blocked [1]. IRS is an electromagnetic two-dimension (2-D) surface composed of a huge number of passive reflecting elements which are fabricated from meta-materials. It depends on altering the phase shift of the incident signals and then reflecting them to their intended destinations without transmitting or receiving signals, thus basically reducing power consumption, hardware cost, and complexity. There are many applications that used IRS- aided wireless communication systems such as physical layer security, a user at dead zone, a user at the cell edge, wireless information power transfer in internet-of-things (IoT) network, and massive device-to-device (D2D) communications [2]. Furthermore, there are many recent techniques that have the same behavior of reflecting the incident signals as the

H. Jin et al. (Eds.): CROWNCOM 2021/WiCON 2021, LNICST 427, pp. 169–180, 2022.
https://doi.org/10.1007/978-3-030-98002-3_12

IRS such as the metasurface or metamaterial reflectors [3, 4], the large intelligent reflecting surface [5–8], and the smart reflect-arrays [9, 10]. Despite the IRS's attractive advantages and applications, there are several challenges that clog using of the IRS in wireless communication systems, but, IRS reflection optimization, IRS deployment, and the IRS channel estimation are the main three challenges. In this survey, we treat the IRS channel estimation challenges.

To leverage the IRS techniques in wireless communications, channel estimation [7, 11−33], is essential because the IRS needs to acquire the CSI to set the reflection coefficients for its elements to reflect the incident signals. But it is the most critical challenge of the IRS due to the IRS's passive and massive elements. This means passive elements without any sensing capabilities to transmit or receive pilot symbols for channel estimation, the massive number of the IRS elements increase the number of paths to be estimated, and the CSI for the whole elements (i.e., full CSI) can't estimate during the limited channel estimation time.

Motivated by the above mentioned in this survey First, we review the main recent techniques used for IRS channel estimation and categorize them into three main methods, which are the cascaded channel estimation method when the IRS elements are fully passive elements, the partial channel estimation method when the IRS surface is equipped with some active elements beside the passive elements for channel estimation purposes, and the explicit channel estimation method when the IRS elements are equipped with some receive radio frequency (RF) chains to make the IRS has sensing capabilities to estimate the CSI. For each method, we explain how can estimate the CSI, show where the channel estimation has occurred (i.e., at the BS, the user, or the IRS), and review the recent related works. Furthermore, in the cascaded channel estimation, there are two manners, the reconstructing the full channel matrix manner and the beam training manner. For the first manner, we design a simple diagram to describe the main processes for IRS channel estimation and data transmission in a simple form. Second, to allow the IRS researchers and interested to clearly and directly acquire information, we summarize our review in a table by listing the current works in the IRS channel estimation ascending with their related methods, techniques, network scenarios, and the achieved outcomes. Lastly, we highlight some important future researches for the IRS channel estimation.

The rest of this paper is organized as follows. Section 2 presents the system model, the IRS channel estimation methods, and their related recent works. Section 3 summarizes the current works for the IRS channel estimation. Section 4 outlines several future works in the IRS channel estimation and Section 5 concludes the paper.

2 IRS Channel Estimation

In the IRS-aided communication systems, the estimate of CSI is quite significant but it is more challenging in practice due to the huge number of its passive elements. This section addresses the main types of IRS channel estimation, reviews, and summarizes the recent works which are carried out to estimate the CSI.

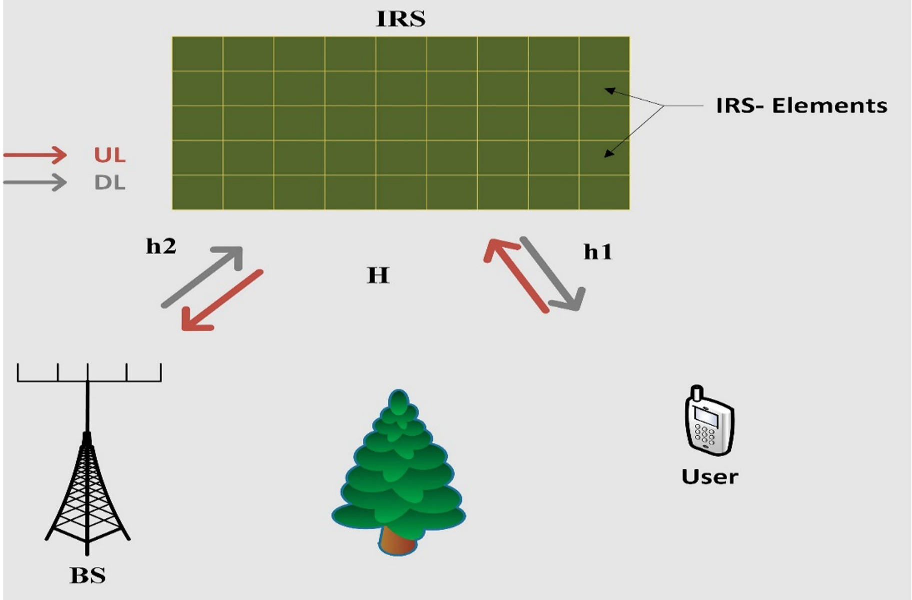

Fig. 1. An IRS-aided communication system

The IRS channel estimation methods are classified based on the type of the IRS elements which are passive, active elements, or elements equipped with some receive RF chains as shown in Fig. 1., into three categories: the cascaded, the partial, and the explicit channel estimation method, respectively.

System Model:
As shown in Fig. 1, the tree is blocking the direct channel between the user and the BS. Therefore, the user communicates with the BS through the IRS under the user-IRS channel (h_1) and IRS-user channel (h_2) which means the cascaded user-IRS-BS channel (H). The IRS consists of M passive reflecting elements each of which reflects the signals to their intended destinations. By considering the uplink (UL) transmission, the received signal Y(t) at the BS is:

$$Y(t) = H\, x(t)\Phi + n(t) \tag{1}$$

Where x(t) is the transmitted signal from the user, H is the cascaded user-IRS-BS channel reflection matrix, Φ is IRS reflection coefficients where $\Phi = \beta m$. Where are the reflection amplitude and the phase shift, respectively, and n(t) is the received noise.

In the following subsections, we present the IRS channel estimation methods one by one in more detail.

2.1 Cascaded Channel Estimation (Fully-passive IRS)

In the cascaded channel estimation, the IRS elements are totally fully passive without any active elements. So, in this case, due to the absence of sensing capabilities, the estimation of cascaded user-IRS-BS channels is a proposed alternative to estimating the IRS BS\user channels directly. in this method, the acquisition of CSI was achieved by using two types of channel estimation manners, reconstructing the full channel matrix and beam training manner.

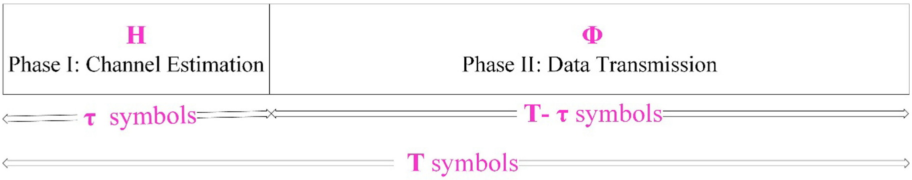

Fig. 2. An IRS-aided channel estimation mode

Reconstructing the Full Channel Matrix Manner

In this manner, the acquisition of the CSI depends on the user\BS' pilot symbols and the IRS's reflection coefficients which are included in the received signals at the BS\user.

Here, the IRS-aided system works in two phases namely the channel estimation phase and data transmission phase as shown in Fig. 2. Under the channel coherence time T symbols, in the channel estimation phase, the users (BS) send their UL (downlink (DL)) pilot symbols (τ symbols) to the IRS for channel estimation and the IRS reflects it to the BS (users). After the BS (users) estimates the channel reflection matrix (H), designs the passive beamforming (Φ), and feeds it (i.e., Φ) back to the IRS in the DL (UL). In the second phase, after adjusting the IRS, the users transmit their data over the residual of the channel coherence time T-τ symbols as shown in Fig. 3.

Related Works

Zheng *et al.* [11] considered an UL OFDM system, they groping the M IRS's passive reflecting elements with high channel correlation into K sub-surfaces to reduce the complexity of channel estimation and reflection design because the IRS's adjacent elements share a common reflection coefficient, this method was extended in [12]. Further, they proposed a full reflection of the IRS during both channel estimation and data transmission phases (i.e., the IRS elements are switched ON all the time).

You *et al.* [12] proposed a novel approach by exploiting the IRS elements grouping and partition, instead of the all-at-once approach which requires a number of pilot symbols depending on IRS elements which means the long length of pilot symbols, hence it increases the channel estimation time. The strategy followed in this work is as follows: the IRS elements are subdivided into K groups, each group partitioned into S sub-groups. First, estimate the CSI for effective channels in each group (per-group effective channel estimation) based on the designed basis training reflection matrix, after that collect the per-group effective channel estimation for each group. Next, resolve the subgroup aggregated channels, (Intra-group channel estimation) based on the designed subgroup training reflection matrix. At the last, from the estimated sub-group aggregated channels of all groups, optimize the passive beamforming vector for

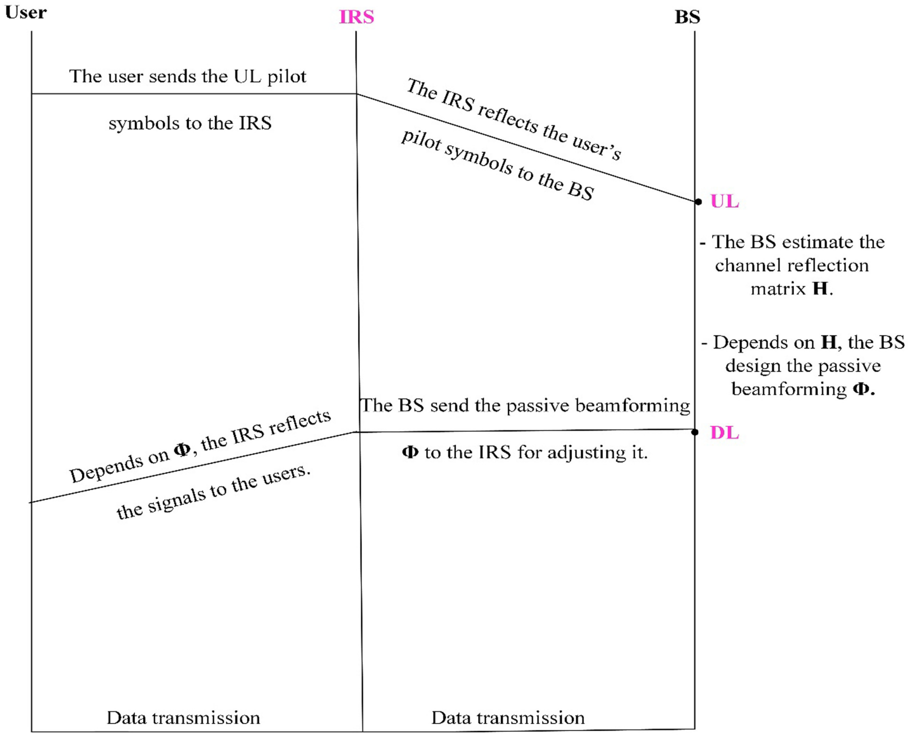

Fig. 3. The basic process to establish the IRS-aided downlink transmission

rate maximization. Here the required number of pilot symbols is reduced to the IRS groups instead of the number of the IRS elements as in the case of all-at-once channel estimation.

He *et al.* [13] introduced a framework for channel estimation with two stages algorithm, a sparse matrix factorization stage, and a matrix completion stage. They formulated the channel estimation problem for the reflected channels h_1 and h_2 from the received signal Y(t) as the matrix factorization problem and solved it by using the bilinear generalized approximate message passing (MiG-AMP) algorithm. Due to the diagonal ambiguity problem of a matrix factorization, they used the matrix completion stage with the Riemannian manifold gradient-based algorithm to solve this problem. Moreover, they provided the joint algorithm of the bilinear factorization (BF) and matrix completion (MC) channel estimation algorithms, which is denoted by (JBF-MC).

Mishra *et al.* [14] considered an ON-OFF state control strategy of IRS which is known as IRS binary reflection, under their proposed channel estimation protocol at each time slot only one IRS element is switched ON and the other elements are switched OFF so, their reflected channels h_1 and h_2 can be estimated one by one without any interference between reflected signals from other elements.

Jensen *et al.* [15] designed a channel estimation scheme to minimize Cramer- Rao lower bound (CRLB) under phase quantization and IRS attenuation constraints by proposing a novel method depends on the minimum variance unbiased estimator where all IRS elements are switched ON during the entire training period compared with the existing ON-OFF state control strategy. Moreover, they Showed that the IRS activation pattern impacts the performance of the channel estimation scheme, which is optimal under this scheme and suboptimal in the ON-OFF schemes.

Wang et al. [16] presented a channel estimation scheme for IRS in the case of the mm-Wave system. To formulation the channel estimation problem they first, exploited the inherent sparsity nature of mm-Wave channels to reduce the training overhead, then, used the Kronecker and Karti-Rao products to find the sparse representation of the cascaded h1 and h2 channels, lastly, they converted the cascaded h1 and h2 channel estimation problem into a sparse signal recovery problem. By applying the compressive sensing (CS) technique, they resolved the channel estimation problem.

The CS is used in signal processing systems to recover the signals by exploiting the property of sparsity of signals with the few numbers of measurements compared by the required sampling theorem. Here, the signal recovering is requiring two conditions to determine which signal recovery is probable, sparsity condition which is based on the sparsity of signal in some domains. And the incoherence condition, which is based on the isometric.

Zheng *et al.* [17] proposed two channel estimation schemes for broadband communication system IRS-aided employing the orthogonal frequency division multiplexing access (OFDMA). The first scheme is the simultaneous user channel estimation (SiUCE) scheme, which estimates the SCI of all users in parallel simultaneously at the BS. The second one is the sequential user channel estimation (SeUCE) scheme, which utilizes the fact that the IRS reflects the signals from all users to the BS via the same channel (IRS-BS channel). Specifically, first estimated the CSI for the arbitrarily selected user (it's called reference user), after that estimated the CSI for remaining users (it's called non-reference users) by normalized the CSI of reference user because the IRS reflected channels are the scale vectors of the reference user and to reduce the channel estimation time. For both schemes they derived minimum training time, the maximum number of supportable users, optimized the training design in terms of user pilot tone allocations and IRS reflection pattern to minimize the channel estimation error. Their results demonstrated that the SiUCE scheme has low complexity compared with the SeUCE scheme but the SiUCE scheme has able to support more users than the SeUCE scheme.

Wang *et al.* [18] proposed a novel pilot-based three-phase channel estimation framework for IRS-aided communication under sequential user channel estimation method by exploiting the correlation among the user-IRS-BS reflected channels of different users, which that each IRS element reflects the signals from all users to the BS via the same channel (as mentioned before). This framework is separated into three phases as follows, Phase I: They switched OFF the IRS and allow the BS to estimate the channel estimation by the traditional method. Phase II: They switched ON the IRS and allow for just one user to send its pilot symbols to the IRS, and IRS reflect it to the BS to estimate the channel estimation. Phase III: They allow for other users to send their pilot symbols to the IRS, and IRS reflects it to the BS to estimate the channel estimation.

Chen *et al.* [19] by utilizing the simultaneous user channel estimation method proposed a protocol for channel estimation in IRS-aided. Under this protocol, they formulated the channel estimation problem as a sparse channel matrix recovery problem using the CS technique to reduce the training overhead. In particular, they proposed a two-step procedure for multi-user channel estimation by exploiting the fact that, the sparse channel matrixes of the cascaded channels of all users have a common row-column block sparsity structure due to the common channel between BS and IRS. In the first step, project the signal into the common column subspace by considering common column-block sparsity to reduce complexity, quantization error, and noise. After that, in the second step, they apply all the projected signals and formulated a multi-user joint sparse matrix recovery problem by considering common row-block sparsity and they proposed an iterative approach to solving this non-convex problem efficiently.

You *et al.* [20] proposed two schemes for channel estimation problem in the case of using double-intelligent reflecting surfaces IRS-aided. The proposed double -IRSs are used to enhance the communication between the user and the BS when the reflected signals from a single IRS cannot pass all the barriers. In this work, they sub-divided the two IRSs elements into sub-surfaces as mentioned before in [11] and proposed two schemes to address the channel estimation problem under cascaded user-IRS1-IRS2-BS double-reflection channels (i.e., the user-IRS1 channel, the IRS1-IRS2 channel, and the IRS2-BS channel). The first scheme for any arbitrary inter-IRS (i.e., IRS1-IRS2) channel and the second scheme is customized under the assumption that the inter-IRS channel is line-of-sight (LOS) dominant. They showed that the second scheme has a smaller normalized mean square error (NMSE) with less channel time training compared with the first scheme.

Elbir *et al.* [21] proposed a framework for IRS channel estimation under mm-Wave massive MIMO systems. They proposed a double convolutional neural network (CNN) based on a deep learning network. The CNN is the joint use of convolutional layers (CL)s and fully connected layers (FCL)s and is fed by three channels data: real, imaginary, and the absolute value of each entry of the received pilot signals for channel estimation.

Elbir *et al.* [22] proposed a channel estimation framework for an IRS-aided massive MIMO system based on federated learning (FL). The proposed FL framework consists of three stages, namely training data collection, model training, and prediction stage. In the first stage, the users collect their training datasets from the received BS' pilot symbols for model training. In the model training stage, the users only transmit the gradients of the model parameters (i.e., model updates) to the BS rather than the whole datasets as in the centralized learning schemes so, the transmission overhead is reduced. After model training, in the prediction stage, users can estimate their channels by feeding the trained model with the received pilot symbols.

Beam Training Manner

In the beam training manner estimation, the passive IRS executes the set of operations that are known to the transceivers. Depending on these operations, the active terminals on the network estimate the channel measurements and then send them to the IRS controller to design the beam patterns “beam directions” for data transmission.

Related Works
Ning *et al*. [23] considered beam training manner for IRS-aided channel estimation. They proposed a hierarchical codebook design for channel estimation and data transmission for a massive MIMO THz communication system. In this scheme, the IRS-aided system operates on two modes, return mode and direction mode. In the return mode: the cascaded transmitter (Tx)-IRS-receiver (Rx) channels are estimated by switching OFF the transmitter and receiver alternately. For the Tx-IRS channel estimation, switch OFF the Rx and allow the IRS to search the narrow beams which are knowns at all terminals on the network. After that, the IRS informed the Tx of the strongest return direction. Then, the Tx-IRS channel is estimated at the Tx. The IRS-Rx channel is estimated by switching OFF the Tx and following the same manner in the Tx-IRS channel estimation. In the direction mode, the Tx or Rx searches for the best direction depending on the estimated Tx-IRS-Rx channels and then sends it to the IRS controller for data transmission. Their work showed that accurate channel estimation can also be obtained by achieving beam training.

2.2 Partial Channel Estimation (Semi-passive IRS)

Here in the partial channel estimation, to facilitate the IRS channel estimation and beamforming reflection, the IRS surface is equipped with some active elements. Thus, the user\Bs sends the pilot symbols to IRS active elements for channel estimation, but in the reflection beamforming stage the active elements work as the residue of the passive elements that reflect the incident signals, and the machine learning techniques are used to learn the IRS how to interact with or reflect the incident signals.

Related Works
Taha *et al*. [24] proposed a novel solution for IRS channel estimation and reflection beamforming problems by using CS and deep learning approaches. In the CS approach after acquiring the channel knowledge at the active elements by using traditional method depending on the UL pilot signals, they developed the CS tools to recover all channels between the IRS and the transmitters/receivers from the channels at active elements (a.k.a sampled channels) without training overhead, and the IRS reflection beamforming vector was obtained by an offline search without beam training. In the deep learning approach, the IRS learns how to interact with the incident signals directly given the estimated sampled channel. This solution operates in two phases, the learning phase and predict phase. The deep learning model is trained through the learning phase while in the predict phase the system learns how to directly reflect the incident signals from the estimated sampled channels with the high data rates.

Their work was extended in [25] by proposing a novel framework by using the deep reinforcement learning (DRL) technique. The DRL is used to adjust the IRS reflection coefficients Φ without training overhead and to adjust the IRS reflection matrix for interacting with the incident signals because the DRL does not require an initial dataset collection phase. For the IRS interaction, the DRL-based IRS framework operates into two phases which are the agent interaction phase and agent learning phase. In the agent interaction phase, the IRS is interacting with the environment as follows: first, the IRS notices the present state (p) of the environment and take an action (c), based on the noticed state, the IRS then obtains a reward (w) for the action (c), lastly a new state notice (p') from the environment. In the agent learning phase, once the experience (p, c, w, p') is obtained, the DRL model is trained by the IRS by the present and past experience.

Liu *et al.* [26] proposed a deep denoising neural network-assisted compressive (CV-DnCNN) model for IRS channel estimation under millimeter-wave (mm-Wave) Massive MIMO system to reduce the training overhead. In this method, they activated some passive elements by equipping a few receive RF chains on it. First, they reconstructed the channel matrix H by using CS after that, they developed the angular-domain common sparsity of mm-Wave MIMO channels over different subcarriers to improve the accuracy, at last, they used their proposal CV-DnCNN for further enhancement. Their proposed model showed that the training overhead can be reduced by increasing IRS active elements and can use it at different signal-to-noise ratios (SNRs).

2.3 Explicit Channel Estimation (IRS Elements Equipped with Some Receive RF Chains)

In this method, the IRS elements are equipped with or connected to some receive RF chains to allow sensing capabilities for the explicit estimation. So, here the explicit channel from user\BS to IRS is estimated at the IRS based on the training signals.

Related Works

Alexandropoulos *et al.* [27] proposed a novel IRS hardware architecture by using a single active receive RF chain. In this architecture, the output of IRS is fed to the receive RF chain to estimate the channel at the IRS. Under the DL transmission, the BS sends its pilot symbols to the IRS to estimate the BS-IRS channel and the user sends its pilot symbols to the IRS to estimate the user-IRS channel. After the IRS was estimated the user-IRS-BS channel, it configured its phase shift and shared it with all of its elements for data transmission. Their simulation results demonstrated that using a single receive RF chain can achieve accurate channel estimation at the IRS.

Based on the above mentioned, the channel estimation in a cascaded manner occurs at the active terminals on the network (i.e., the BS or the user) and is achieved by the user\BS' pilot symbols or the beam training. In the channel estimation partial manner, it occurs at the IRS active elements based on the user\BS' pilot symbols. But in the explicit channel estimation manner, it occurs at the IRS depending on both user and BS' pilot symbols.

3 Summary

In this section, we summarize and classify the recent works of IRS channel estimation in a specific form as listed in Table 1. The summary includes five directions each of which has some classifications as follows: the IRS channel estimation method is based on cascaded, partial, or explicit channel estimation methods as we mentioned before in

Sect. 2, the IRS channel estimation problem formulation method which includes learning, mathematical and beam training method, the IRS reflection pattern depends on binary reflection or full reflection, the network context depends on the number of users (single-user or multi-user) and the type of the transmission (UL or DL transmission), and the evaluation of system performance which includes estimation error such as NMSE, mean-squared error (MSE), or least-squares (LS) and quantization error.

Table 1. Summary of the recent works of IRS channel estimation

Survey	Year	Scope															
		IRS channel estimation method			Problem formulation method			IRS reflection pattern		The Network context				System performance evaluation method			
		Cascaded channel estimation	Partial channel estimation	Explict channel estimation	Learning method	Mathimatical method	Beamtraining method	Binary reflection	Full reflection	Single-user	Multi-user	UL	DL	NMSE	LS	MSE	Quantization Erorr
Taha *et al.* [25]	2019		√		√				√	√		√				√	
Mishra *et al.* [14]	2019	√				√		√		√		√			√		
Chen *et al.* [19]	2019	√				√		√			√	√		√	√		
He *et al.* [13]	2019	√				√		√		√		√		√			
Jensen *et al.* [15]	2019	√				√		√	√		√	√				√	
You *et al.* [12]	2020	√				√		√	√	√		√		√			
Zheng *et al.* [11]	2020	√				√		√	√	√		√		√			
Elbir *et al.* [21]	2020	√			√			√			√		√	√	√		
Liu *et al.* [26]	2020		√		√				√	√		√		√			
Wang *et al.* [16]	2020	√				√		√	√		√	√		√			
Elbir *et al.* [22]	2020	√			√			√			√		√	√			
Zheng *et al.* [17]	2020	√				√		√			√	√		√			
You *et al.* [20]	2020	√				√		√	√	√		√		√			
Taha *et al.* [24]	2020		√		√				√	√		√				√	
Wang *et al.* [18]	2020	√				√		√	√	√			√	√			
Alexandropoulos *et al.* [27]	2020			√		√			√	√			√	√	√		
Ning *et al.* [23]	2020	√					√	√		√			√				√

4 Future Research

In the next few years, we expect that the IRS will change the face of wireless communications by combining active and passive terminals in one network. But until now, the acquiring of accurate CSI in practice still it is an open problem. So, the most important research direction is how to execute the existing IRS channel estimation proposals practically in the real world.

The second direction is in terms of estimating the channels related to all users in IRS-aided multi-user communication schemes, how to minimize the channel estimation time to maximize the data transmission time. The last direction is how to optimize the existing channel estimation scenarios in case of IRS elements grouping and partition to obtain high performance with low complexity, minimum channel estimation time, and minimum training overhead.

5 Conclusion

This survey presented an overview of channel estimation for IRS-aided communication systems, reviewed the recent related works, and highlighted the important future research directions for IRS channel estimation. We hope this survey becomes helpful in future research in this field and contributes to facilitating the IRS' challenges.

Acknowledgement. This work was supported in part by Shanghai Rising-Star Program under Grant 19QA1409100, in part by the National Natural Science Foundation of China under Grants 62071332, 61631017, and U1733114, and in part by the Fundamental Research Funds for the Central Universities. I would like to express my very great appreciation to Pr. Huang for his valuable and constructive suggestions during the planning and development of this research work. His willingness to give his time so generously has been very much appreciated.

References

1. Zhao, J.: A survey of intelligent reflecting surfaces (IRSs): Towards 6G wireless communication networks. https://arxiv.org/abs/1907.04789 (2019)
2. Wu, Q., Zhang, R.: Towards smart and reconfigurable environment: intelligent reflecting surface aided wireless network. IEEE Commun. Mag. **58**(1), 106–112 (2020). https://doi.org/10.1109/MCOM.001.1900107
3. Zhang, L., et al.: Space-time-coding digital metasurfaces. Nat. Commun. **9**(1), 4334 (2018)
4. Zhao, J., et al.: Programmable time-domain digital-coding metasurface for non-linear harmonic manipulation and new wireless communication systems. Natl. Sci. Rev. **6**(2), 231–238 (2018)
5. Hu, S., Rusek, F., Edfors, O.: Beyond massive MIMO: The potential of data transmission with large intelligent surfaces. IEEE Trans. Signal Process. **66**(10), 2746–2758 (2018)
6. Hu, S., Rusek, F., Edfors, O.: Beyond massive MIMO: The potential of positioning with large intelligent surfaces. IEEE Trans. Signal Process. **66**(7), 1761–1774 (2018)
7. Han, Y., Tang, W., Jin, S., Wen, C.-K., Ma, X.: Large intelligent surface-assisted wireless communication exploiting statistical CSI. IEEE Trans. Veh. Technol. **68**(8), 8238–8242 (2019). https://doi.org/10.1109/TVT.2019.2923997
8. Nadeem, Q.U.A., Kammoun, A., Chaaban, A., Debbah, M., Alouini, M.S.: Asymptotic analysis of large intelligent surface assisted MIMO communication. https://arxiv.org/abs/1903.08127 (2019)
9. Nie, S., Jornet, J.M., Akyildiz, I.F.: Intelligent environments based on ultra-massive MIMO platforms for wireless communication in millimeter wave and terahertz bands. In: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 7849–7853 (2019)
10. Tan, X., Sun, Z., Jornet, J.M., Pados, D.: Increasing indoor spectrumsharing capacity using smart reflect-array. In: IEEE International Conference on Communications (ICC), pp. 1–6 (2016)
11. Zheng, B., Zhang, R.: Intelligent reflecting surface-enhanced OFDM: Channel estimation and reflection optimization. IEEE Wireless Commun. Lett. **9**(4), 518–522 (2020)
12. You, C., Zheng, B., Zhang, R.: Intelligent reflecting surface with discrete phase shifts: Channel estimation and passive beamforming. In: Proceedings IEEE International Conference. Communications (ICC), Dublin, Ireland, June, pp. 1–6 (2020)
13. He, Z.-Q., Yuan, X.: Cascaded channel estimation for large intelligent metasurface assisted massive MIMO. IEEE Wireless Commun. Lett. **9**(2), 210–214 (2020)
14. Mishra, D., Johansson, H.: Channel estimation and low-complexity beamforming design for passive intelligent surface assisted MISO wireless energy transfer. In: International Conference on Acoustics, Speech and Signal Processing (ICASSP*)*, May 2019
15. Jensen, T.L., De Carvalho, E.: On optimal channel estimation scheme for intelligent reflecting surfaces based on a minimum variance unbiased estimator. https://arxiv.org/abs/1909.09440 (2019)

16. Wang, P., Fang, J., Duan, H., Li, H.: Compressed channel estimation for intelligent reflecting surface-assisted millimeter wave systems. IEEE Signal Process. Lett. **27**, 905–909 (2020). https://doi.org/10.1109/LSP.2020.2998357
17. Zheng, B., You, C., Zhang, R.: Intelligent reflecting surface assisted multi-user OFDMA: Channel estimation and training design. http://arxiv.org/abs/2003.00648
18. Wang, Z., Liu, L., Cui, S.: Channel estimation for intelligent reflecting surface assisted multiuser communications: Framework, algorithms, and analysis. IEEE Trans. Wireless Commun. (2020). https://doi.org/10.1109/TWC.2020.3004330
19. Chen, J., Liang, Y.C., Cheng, H.V., Yu, W.: Channel estimation for reconfigurable intelligent surface aided multi-user MIMO systems. https://arxiv.org/abs/1912.03619
20. You, C., Zheng, B., Zhang, R.: Wireless communication via double IRS: channel estimation and passive beamforming designs. IEEE Wireless Commun. Lett. **10**(2), 431–435 (2021). https://doi.org/10.1109/LWC.2020.3034388
21. Elbir, A.M., Papazafeiropoulos, A., Kourtessis, P., Chatzinotas, S.: Deep channel learning for large intelligent surfaces aided mm-wave massive MIMO systems. IEEE Wireless Commun. Lett. **9**(9), 1447–1451 (2020)
22. Elbir, A.M., Coleri, S.: Federated learning for channel estimation in conventional and IRS-assisted massive MIMO. https://arxiv.org/abs/2008.10846 (2020)
23. Ning, B., Chen, Z., Chen, W., Du, Y.: Channel estimation and transmission for intelligent reflecting Surface assisted THz communications. arXiv e-prints (2019)
24. Taha, A., Alrabeiah, M., Alkhateeb, A.: Enabling large intelligent surfaces with compressive sensing and deep learning. arXiv preprint https://arxiv.org/abs/1904.10136, Apr 2019
25. Taha, A., Zhang, Y., Mismar, F.B. and Alkhateeb, A.: Deep reinforcement learning for intelligent reflecting surfaces: towards standalone operation.https://arxiv.org/abs/2002.11101, May 2020
26. Liu, S., Gao, Z., Zhang, J., Renzo, M.D., Alouini, M.: Deep denoising neural network assisted compressive channel estimation for mmWave intelligent reflecting surfaces. IEEE Trans. Veh. Technol. **69**(8), 9223–9228 (2020)
27. Alexandropoulos, G.C., Vlachos, E.: A hardware architecture for reconfigurable intelligent surfaces with minimal active elements for explicit channel estimation. arXiv e-prints (2020)
28. Zhao, M.M., Wu, Q., Zhao, M.J., Zhang, R.: Two-timescale beamforming optimization for intelligent reflecting surface enhanced wireless network. In: 2020 IEEE 11th Sensor Array and Multichannel Signal Processing Workshop (SAM), pp. 1–5 (2020). https://doi.org/10.1109/SAM48682.2020.9104346
29. You, C., Zheng, B., Zhang, R.: Fast beam training for IRS-assisted multiuser communications. IEEE Wireless Commun. Lett. **9**(11), 1845–1849 (2020)
30. Wu, Q., Zhang, R.: Intelligent reflecting surface enhanced wireless network: joint active and passive beamforming design. IEEE Global Commun. Conf. (GLOBECOM) **2018**, 1–6 (2018). https://doi.org/10.1109/GLOCOM.2018.8647620
31. Lin, J., et al.: Channel estimation for wireless communication systems assisted by large intelligent surfaces. arXiv preprint https://arxiv.org/abs/1911.02158 (2019)
32. Wei, L., Huang, C., Alexandropoulos, G.C., Yuen, C.: Parallel factor decomposition channel estimation in RIS-assisted multi-user MISO communication. In: 2020 IEEE 11th Sensor Array and Multichannel Signal Processing Workshop (SAM), pp. 1–5 (2020). https://doi.org/10.1109/SAM48682.2020.9104305
33. Hu, R., Tong, J., Xi, J., Guo, Q., Yu, Y.: Matrix completion-based channel estimation for MmWave communication systems with array-inherent impairments. IEEE Access **6**, 62915–62931 (2018). https://doi.org/10.1109/ACCESS.2018.2877432