Doppler Shift and Channel Estimation for Intelligent Transparent Surface Assisted Communication Systems on High-Speed Railways

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Abstract—The emerging intelligent transparent surface (ITS), unlike the intelligent reflection surface (IRS), allows incident signals to penetrate it instead of being reflected, which enables the ITS to combat the severe signal penetration loss for high-speed railway (HSR) wireless communications. This paper thus investigates the channel estimation problem where the ITS is attached to the HSR carriage window. We first propose a new transmission scheme with two pilot blocks for each frame. Second, we formulate the channels as functions of physical parameters and thus transform the problem into a parameter recovery problem. Third, we develop a successive closed-form, maximum likelihood (ML) channel estimation algorithm. Specifically, each estimate is expressed as the sum of its perfectly known value and the estimation error. By leveraging the relationship between channels for the two pilot blocks, we eliminate the unknown parameters besides Doppler shifts, which can be thereby recovered. With the reconstructed Doppler-induced phase shifts, we acquire other channel parameters. Moreover, the Cramér-Rao lower bound (CRLB) for each parameter is derived as a performance benchmark. Finally, we provide numerical results to establish the effectiveness of our proposed estimators.

Index Terms—Channel estimation, Cramér-Rao lower bound (CRLB), Doppler shift, high-speed railway (HSR) communications, intelligent transparent surface (ITS), maximum likelihood (ML) principle.

I. INTRODUCTION

HIGH-SPEED railway (HSR) greatly facilitates the daily commutes of millions of people with less energy consumption and air pollution than conventional transportation systems [1], [2]. One of the crucial parts of HSR operations and economic viability is the onboard availability of wireless communication systems, which not only safeguards train operations but also delivers modern communication services and applications to passengers. Nonetheless, one critical hindrance to HSR communications is the extreme penetration loss [3]. The body of train carriages is typically made of aluminum, which significantly attenuates electromagnetic (EM) waves. Thus, the carriage windows are the main paths for transmission [4]. Unfortunately, the industry has adopted coated windowpanes for thermal insulation and energy saving [5], resulting in a severe penetration loss of over 20 dB to EM waves propagating through windows at the same time [6]. Traditional solutions to this issue include relay [7] and multiple-input multiple-output (MIMO) technology [8], both of which however, incur high energy consumption, implementation complexity, and hardware cost. With the rapid development of technology, HSR communication has been evolving into an intelligent era [9], where we seek new and promising methods to address the forgoing challenge.

Recently, the intelligent reflection surface (IRS) and its various equivalents have drawn extensive attention as a spectrum- and energy-efficient technology to smartly reconfigure the radio propagation environment for 5G/6G wireless communication systems [10], [11], [12]. An IRS is generally a planar metasurface comprising numerous passive reflection elements, each one being customizable to change the amplitude and phase shift of the incident signals [13], [14], [15]. Therefore, the IRS enables the amplification of desirable incoming signals with low power consumption by constructively superimposing the reflected signals on those non-reflected ones [16], [17]. In addition, the IRS has massive advantages from the implementation aspect, e.g., scalable cost, lightweight, conformal geometry, excellent compatibility, and others [18], [19], [20].

The existing works on the IRS-assisted wireless communications with high-mobility users (inside highway cars, trains, etc.) mainly consider employing stationary IRS panels (see, e.g., [21], [22], [23], [24]). Nevertheless, without a dedicated energy supply, the signal coverage of the IRS is much smaller than that of the active transceiver; hence, the service time of each static IRS for fast-moving users becomes severely limited. To address this issue, the work [25] considers deploying IRSs on controllable unmanned aerial vehicles (UAVs) to follow mobile users. This proposal is practically difficult for

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the UAV operations to maintain the IRS-based services to users during their entire movements, especially in the interested HSR scenario with a wide area and complex environment. In a nutshell, the passive and reflective properties of the IRS might constrain its applications for high-mobility users.

To this end, instead of utilizing the reflection capability of the metasurface, we further consider a new type of intelligent manufactured surface comprising multiple passive refraction elements, named intelligent transparent surface (ITS) [26]. That is, ITS enables tunable penetration rather than reflection for incident signals while inheriting the other various advantages of IRS. The comparison between the refractive ITS and the reflective IRS is illustrated in Fig. 1, where an ITS and an IRS are deployed on the $xy$-plane and $yz$-plane respectively to serve a static user equipment (UE) connected with the base station (BS). With the functionality of adjustable transmission, we consider attaching ITS to the train window to assist the wireless communications of UE inside the carriage (Fig. 2). This way, since the ITS travels with the train, the fast-moving UE can be easily covered by ITS-refracted signals, significantly, along the entire HSR lines. By further suitably designing the passive beamforming employed at the ITS, we can not only enhance the desirable signals but also maintain the amplification to combat the penetration loss in HSR communications. It is worth noting that the ITS has been referred to as other terminologies in the literature, such as transmissive metasurface [27], intelligent refraction surface [28], [29], refractive/transmissive reconfigurable intelligent surface [30], [31], among others.

One solution to the hardware implementation of ITS is based on dielectric metasurfaces, which can realize the complete control of transmission amplitude, phase, and polarization [32], [33], [34], [35]. Specifically, the metasurface comprises multiple dielectric unit cells, and one or several meta-atoms made of high-refractive-index amorphous silicon are placed at the centers of each cell. By properly designing the parameters of meta-atoms, such as the geometrical shape (e.g., elliptical, C-shaped, or X-shaped pillar), thickness, orientation, inter-cell spacing, etc., the transmission functionalities of each ITS element can be arbitrarily controlled. In addition, similar to the IRS, an intelligent controller can adjust the refraction coefficients of ITS in real time to follow the time-varying wireless channel. Electronic switches in practice can realize this, including diodes, field-effect transistors (FETs), micro-electromechanical system (MEMS) devices, and so on [36].

The channel state information (CSI) is the fundamental knowledge needed for the optimal design of ITS beamforming. Note that several works have treated the channel estimation problem for ITS-aided high-mobility communication systems [26], [27], [28], [29], [37]. Specifically, the work [26] investigated the joint effective channel estimation and information data detection scheme and performed a theoretical analysis of this iterative algorithm. Reference [27] further combined the orthogonal time frequency space (OTFS) modulation with ITS technology. Moreover, it proposed a joint estimator of channels and Doppler-induced phase shifts for each BS-UE propagation path based on the majorization-minimization (MM) method. The work [28] developed an efficient two-stage transmission protocol to perform channel estimation and ITS beamforming for data transmission. Therein, both channels for the BS-ITS link and ITS-UE link were assumed to be line-of-sights (LoSs) and formulated as the functions of channel parameters to be estimated. In contrast, the direct BS-UE link channel was fast fading because of various propagation paths. We note that the authors in [28] extended their work into the general case with the BS-ITS link modeled as a multi-path fading channel, as well as with uniform planar array (UPA) structure at ITS instead of the previous assumption uniform linear array (ULA) [29]. Furthermore, the work [37] simplified [28] by considering the direct BS-UE link as LoS type and then proposed the enhanced transmission protocol with less pilot overhead and low-complexity parameter estimators for the direct link. Meanwhile, the remaining issues of these works [28], [29], [37] are mentioned below:

- These three works exploited the two-dimensional (2D) grid-based exhaustive search once or more to estimate the channel parameters for the cascaded BS-ITS-UE link. Reference [29] refined the estimates via gradient-based search. Since both performances of the two search-based methods above are directly proportional to the searching precision, considerable computation complexity and time
consumption inevitably accompany the desirable performance of CSI estimation.

- In [29], the direct BS-UE channel and cascaded BS-ITS-UE channel were repeatedly estimated even in the data transmission stage owing to their time-varying properties, resulting in extra training sequence consumption and reduced transmission efficiency.

- In [37], during each training block, the direct channel was obtained at first by switching off ITS, and next, the cascaded channel could be recovered based on the direct channel estimate with the ITS switched on. This method not only enlarges the implementation complexity for the continuous switchover but also degrades the estimation performances of cascaded channels.

- References [28] and [37] could only obtain the indispensable CSI for ITS beamforming design after the first at least three blocks within each frame under the assumption of ULA framework at ITS (at least four blocks for UPA), postponing the significant beamforming gain for data transmission.

Motivated by the above, we study the design problems of the transmission scheme and channel estimation algorithm for the ITS-aided HSR communication system (Fig. 2). Since the LoS component is dominant in HSR wireless because of the limited multipath scattering and signal diffraction from obstacles [2], [38], we assume that both BS-UE and BS-ITS channels are LoS types, which is the same assumption made in [37]. Based on the system model in [28], we represent all three channels for the links BS-UE, BS-ITS and ITS-UE with different physical parameters, and we transform the channel estimation into a parameter recovery problem. The main contributions of this paper are summarized as follows:

- We propose a new two-phase transmission scheme with ITS consistently turned on. Within each frame, only the first two blocks are designed for pilot transmission, which suffice for the complete high-accuracy parameter estimation; the subsequent blocks are all used for data transmission with beamforming performed at ITS, and the channels applied to data detection can be constructed via the estimates of channel parameters. To facilitate the channel estimation, every pilot block is further divided into subblocks with each containing the training sequence of identical length, and the refraction coefficients of ITS during every training pilot are carefully pre-designed.

- We develop a serial channel estimation algorithm in closed form by leveraging the classical maximum likelihood (ML) principle. Herein, we first precisely obtain the channel estimates for the direct BS-UE link and the cascaded BS-ITS-UE link, and formulate each channel estimate with its true value and estimation error. By utilizing the relation between channels for the two pilot blocks, the unknown parameters can be eliminated besides Doppler shifts, which can be hence obtained. With the help of the Doppler estimates, we can further estimate other channel parameters.

- We derive the Cramér-Rao lower bounds (CRLBs) for each channel parameter to appraise the performances of the proposed estimators. Numerical results indicate that our estimators approach or even attain their corresponding CRLBs, which demonstrates the performance effectiveness. Furthermore, the superiority of our channel estimation algorithm is also verified by simulation comparisons with benchmarking algorithms proposed in [28] and [37].

The remainder of this paper is organized as follows. Section II presents the transmission scheme, introduces the system model, and identifies the channel parameters to be estimated. Section III proposes the coefficient design of the ITS and the ML-based channel estimation algorithm. Useful discussions can be found in the same section. In Section IV, we derive the CRLBs for our estimators. Section V provides numerical results to corroborate our studies. Finally, this paper is concluded in Section VI.

Notations: Scalars, column vectors, and matrices are denoted by italic letters, bold-face lower-case letters, and bold-face upper-case letters, respectively. Upper-case Calligraphy letters (e.g., $\mathcal{K}$) denote discrete and finite sets. $\mathbb{R}^{M \times N}$ and $\mathbb{C}^{M \times N}$ denote the domain of $M \times N$ real and complex matrices, respectively. The transpose, conjugate transpose, inverse, pseudo-inverse, trace, and determinant of $\mathbf{A}$ are denoted by $\mathbf{A}^T$, $\mathbf{A}^H$, $\mathbf{A}^{-1}$, $\mathbf{A}^\dagger$, $\text{tr} (\mathbf{A})$ and $\text{det} (\mathbf{A})$, respectively, and $[\mathbf{A}]_{m,n}$ denotes the $(m,n)$th entry. For complex-valued $\mathbf{x}$, $\mathbb{R} (\mathbf{x})$, $|\mathbf{x}|$, $\angle \mathbf{x}$ and $e^{\mathbf{x}}$ denote the vectors with each entry being the real part, amplitude, argument, and exponential function of the corresponding entry in $\mathbf{x}$, respectively, and $j$ denotes the imaginary unit, i.e., $j^2 = -1$. For any general vector $\mathbf{x}$, $[\mathbf{x}]_m$ denotes the $m$th entry, $\text{diag} (\mathbf{x})$ denotes a square diagonal matrix with the elements of $\mathbf{x}$ on the main diagonal, and $\| \mathbf{x} \|_\ell$ denotes the $\ell$-norm. $\mathbf{1}_{M \times N}$, $\mathbf{0}_{M \times N}$ and $\mathbf{I}_M$ denote an all-one matrix of size $M \times N$, an all-zero matrix of size $M \times N$ and the identity matrix of size $M \times M$, respectively. $\odot$ and $\otimes$ denote the Hadamard and Kronecker product, respectively, and $\mathbb{E}_x \{ \cdot \}$ denotes the statistical expectation over random $\mathbf{x}$. $\mathcal{CN} (\mathbf{\mu}, \mathbf{\Sigma})$ denotes the distribution of a complex Gaussian random vector with mean $\mathbf{\mu}$ and covariance matrix $\mathbf{\Sigma}$. $\sim$ and $\triangleq$ stand for “distributed as” and “defined as”, respectively. Finally, “independently and identically distributed” is abbreviated as “i.i.d.”.

II. PROBLEM FORMULATION

As shown in Fig. 2, we consider an ITS-aided HSR wireless communication system, where an ITS is attached to the carriage window to assist in the downlink communications from a BS to a UE inside the carriage. The train is moving at a high speed of $v$ with respect to the static BS. For ease of exposition, we assume that both the BS and UE are single-antenna radios.\(^1\) Moreover, the ITS positioned on the $yz$-plane can be treated as a UPA comprising $M = M_y \times M_z$ refraction elements. The BS can separately control their amplitudes and phase shifts in real time through an intelligent controller.

We propose a new two-phase transmission scheme (Fig. 3) for the ITS-aided HSR communication system. Specifically,

\(^1\)As for the general CSI case for a multiple-antenna BS, each antenna can be turned on in succession within every two enhanced pilot blocks to perform channel estimation individually.
this scheme divides each frame with \( K \) blocks into the estimation and transmission phases, comprising two pilot blocks and \( K - 2 \) data blocks, respectively. Furthermore, every pilot block comprises \( I \) subblocks, with each comprising \( N \) training pilots.\(^2\) Since channel estimation is the goal here, we only concentrate on the first two pilot blocks of one typical frame in the rest of this paper. The ITS beamforming design during the transmission phase will be forthcoming in our future work.

### A. Channel Model

Because of the high-speed relative mobility between the BS and train, both the BS-UE and BS-ITS links suffer from severe Doppler frequency shifts. Denote the baseband equivalent channels for these two forgoing links during the \( i \)-th subblock of block \( k \) by \( g_{k,i} \) and \( b_{k,i} \in \mathbb{C}^{M \times 1} \), respectively, \( k \in K \triangleq \{0, 1\} \) and \( i \in I \triangleq \{0, \ldots, I - 1\} \). Moreover, let \( u \in \mathbb{C}^{M \times 1} \) represent the equivalent baseband channel for the ITS-UE link, which stays unchanged within each frame since, in this short period, the ITS and UE are assumed to be relatively static. Like [37], we assume that the three channels for BS-UE, BS-ITS, and ITS-UE links are all LoS types, as mentioned earlier. Here, the channel \( g_{k,i} \) through the train window can be expressed as

\[
g_{k,i} = e^{j2\pi f_{dl}(kI+i)T} \rho_{BU} f_w, \tag{1}
\]

where \( f_{dl} = \frac{c}{2} \sin \theta_T \sin \delta_T \) denotes the Doppler shift on the BS-UE link, with \( \lambda \) being the signal wavelength and \( \theta_T (\delta_T) \) denoting the azimuth (elevation) angle of arrival (AoA) at the UE, \( T \) represents the duration of each subblock, the complex-valued parameter \( \rho_{BU} \) is the propagation gain for the link BS-UE, and \( f_w \) denotes the complex penetration gain through the carriage window. For the convenience of exposition, we define \( \beta_1 \triangleq \rho_{BU} f_w \) as the path gain for the direct BS-UE link. In addition, the channel \( b_{k,i} \) can be modelled as

\[
b_{k,i} = e^{j2\pi f_{dl}(kI+i)T} \rho_{BI} (a_y(\varphi_y^t) \otimes a_z(\varphi_z^t)), \tag{2}
\]

where \( f_{dl} = \frac{c}{2} \sin \theta_T \sin \delta_T \) is the Doppler shift on the BS-ITS link with \( \varphi_y^t (\varphi_z^t) \) being the azimuth (elevation) AoA at the ITS, and \( \rho_{BI} \) is the complex propagation gain between the BS and ITS. The vector \( a^t(\varphi_T^t, \delta_T^t) \) represents the receive array response of the ITS on the \( yz \)-plane, \( a_y(\varphi_y^t) \triangleq [1, e^{j\varphi_y^t}, \ldots, e^{j(M_T-1)\varphi_y^t}]^T \) and \( a_z(\varphi_z^t) \triangleq [1, e^{j\varphi_z^t}, \ldots, e^{j(M_z-1)\varphi_z^t}]^T \) are the one-dimensional (1D) steering vectors on the \( y \)-axis and \( z \)-axis, respectively, where \( \varphi_y^t \triangleq \frac{2\pi}{\lambda} d \sin \theta_T \sin \delta_T \) and \( \varphi_z^t \triangleq \frac{2\pi}{\lambda} d \cos \delta_T \) represent the phase differences between two adjacent elements, and \( d \) denotes the inter-element spacing equal to half-wavelength. We assume that the moving distance of train during one transmission frame is negligible compared to the distance between the BS and train, and hence the geometry-related channel parameters \( \{f_{dl}, \rho_{BU}, f_w, f_{dl}^2, \rho_{BI}, \varphi_y^t, \varphi_z^t\} \) in (1) and (2) can be approximately treated as constants within the considered frame [28], [29]. Similarly, the channel \( u \) is presented as

\[
u = \rho_{BU} a_y(\varphi_y^t) \otimes a_z(\varphi_z^t), \tag{3}\]

where \( \rho_{BU} \) denotes the complex propagation gain for the ITS-UE link, and the transmit array response of the ITS \( a^t(\varphi_T^t, \delta_T^t) \) at an azimuth (elevation) angle of departure (AoD) \( \varphi_T^t (\delta_T^t) \) is defined in the same way as the receive array response \( a^t(\varphi_T^t, \delta_T^t) \). Herein, the Doppler shift vanishes owing to the relatively motionless assumption as opposed to (1) and (2).

Let us define \( \phi_{k,i} = [\phi_{k,i}^{(0)}, \ldots, \phi_{k,i}^{(M-1)}] \in \mathbb{C}^{M \times 1} \) as the ITS refraction vector within subblock \( i \) of block \( k \) and we assume that every amplitude coefficient can be set as \( |\phi_{k,i}^{(m)}| = 1 \) to neglect the signal power loss through the ITS.\(^3\) \( m \in \{0, \ldots, M - 1\} \). As such, the effective channel \( \tilde{h}_{k,i} \) for the cascaded BS-ITS-UE link through both window and ITS is given by

\[
\tilde{h}_{k,i} = f_w (b_{k,i} \otimes u)^T \phi_{k,i} \tag{4}
\]

where \( \beta_2 \triangleq \rho_{BU} f_w \) denotes the path gain for the cascaded link, and \( a \) is the equivalent array response vector at the ITS, which is expressed as

\[
(\text{a}) \quad a = (a_y(\varphi_y^t) \otimes a_z(\varphi_z^t)) \otimes (a_y(\varphi_y^t) \otimes a_z(\varphi_z^t))
\]

\[
(a) \quad a = (a_y(\varphi_y^t) \otimes a_y(\varphi_y^t)) \otimes (a_z(\varphi_z^t) \otimes a_z(\varphi_z^t))
\]

\[
(b) \quad a = (a_y(\varphi_y^t) \otimes a_z(\varphi_z^t)), \tag{5}
\]

where \( \text{(a)} \) is the result of using the mixed property of Kronecker and Hadamard products, \( \text{(b)} \) is obtained as we perform the Hadamard product and then define \( \varphi_y \triangleq \varphi_y^t + \varphi_y^t \) and \( \varphi_z \triangleq \varphi_z^t + \varphi_z^t \) as the equivalent inter-element phase differences on the \( y \) and \( z \) axes, respectively.

\(^2\)The minimum quantity of pilot symbols within each frame will be discussed at the end of Section III.

\(^3\)The amplitude coefficient of a refractive/reflective metasurface element depends on its exact design, including structure, material, voltage, and others. The frequency of incoming signals also impacts it. Specifically, existing metasurface prototypes can achieve the amplitude efficiency of 85%–99% [32] or 80%–95% [40] or 70%–98% [41] in the reflection mode.

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B. Signal Model

Let \( N \triangleq \{0, \ldots, N-1\} \) denote the index set of training symbols during each subblock. We further consider that the ITS refraction coefficients are adjusted symbol by symbol, and the corresponding symbol-varying refraction vector, say \( \phi_{k,i,n} \), is designed as

\[
\phi_{k,i,n} = \psi_{k,i,n} \phi_{k,i},
\]

where \( \phi_{k,i} \) denotes the initial refraction vector dedicated to subblock \( i \) of block \( k \), and \( \psi_{k,i,n} \) is the adjustment coefficient during every pilot \( n \in N \).

As the transmitted signal from the BS can propagate to the UE through the direct BS-UE link and the cascaded BS-ITS UE link, the received signal within symbol \( n \) of subblock \( i \) emitted at block \( k \) is given by

\[
y_{k,i,n} = (g_{k,i} + \psi_{k,i,n} h_{k,i}) x_{k,i,n} + w_{k,i,n},
\]

where \( x_{k,i,n} \) denotes the training symbol which is designed as \( x_{k,i,n} = 1 \) for the exposition simplicity, \( w_{k,i,n} \sim C\mathcal{N}(0, \sigma^2) \) denotes the i.i.d. complex Gaussian noise at the UE, and \( h_{k,i} \) represents the initial cascaded channel during each subblock, i.e.,

\[
h_{k,i} = e^{j2\pi f_d(k+1+i)T} \beta_2 a^T \bar{\phi}_{k,i}.
\]

Remark 1: Our target now is to estimate the unknown channel parameters, including (i) Doppler shifts \( \{f_{d0}, f_{d2}\} \), (ii) path gains \( \{\beta_1, \beta_2\} \), and (iii) equivalent phase differences at ITS \( \{\varphi_1, \varphi_2\} \). Once the parameter recovery issue is completed using the received pilot symbols, we can perform the beamforming design at ITS and construct the parameterized channel estimates for data detection during the subsequent data transmission phase (Fig. 3).

III. CHANNEL ESTIMATION ALGORITHM

A. Channel Estimation

We start by tackling the estimation problem of channels \( g_{k,i} \) and \( h_{k,i} \) with \( k \in K \), \( i \in I \). To facilitate the channel estimation, the refraction coefficients of ITS are pre-designed with the aid of (6) by letting \( \psi_{0,i,n} = \psi_{1,i,n} \) and \( \phi_{0,i} = \phi_{1,i} \) for all \( i \) and \( n \), and thus we have \( \phi_{0,i,n} = \phi_{1,i,n} \). In this case, we omit their subscript \( k \) henceforth for notational simplicity. When the transmission of subblock \( i \) during block 1 comes to an end, stack \( 2N \) received pilot symbols \( \{g_{0,i,n}\}_{n=0}^{N-1} \) and \( \{y_{1,i,n}\}_{n=0}^{N-1} \) within the \( i \)-th subblocks of both block 0 and block 1, then the received signal can be expressed in vector form as

\[
Y_i = \Psi_i V_i + W_i,
\]

where \( Y_i = [y_{0,i}, y_{1,i}] \in \mathbb{C}^{N \times 2} \) denotes the received symbol matrix with \( y_{k,i} = [h_{k,i,0}, \ldots, h_{k,i,N-1}]^T \in \mathbb{C}^{N \times 1} \). \( \Psi_i \in [1_{N \times 1}, \psi_i] \in \mathbb{C}^{N \times 2} \) represents the training matrix with \( \psi_i = [\psi_{0,i}, \ldots, \psi_{i,N-1}]^T \in \mathbb{C}^{N \times 1} \), \( V_i = [v_{0,i}, v_{1,i}] \in \mathbb{C}^{2 \times 2} \) is the channel matrix to be estimated with \( v_{k,i} = [g_{k,i}, h_{k,i}]^T \), and denote the received noise matrix by \( W_i = [w_{0,i}, w_{1,i}] \in \mathbb{C}^{N \times 2} \) with \( w_{k,i} = [w_{k,i,0}, \ldots, w_{k,i,N-1}]^T \in \mathbb{C}^{N \times 1} \).

By proper design of the training matrix \( \Psi_i \), we can construct a full-rank tall rectangular matrix, namely \( \Psi_i^T \) exists.

In this paper, we draw the first and another columns of the \( N \)-point discrete Fourier transform (DFT) matrix with \( [F_N]_{t_1, t_2} = e^{-j2\pi t_1 t_2/N} \) for \( 0 \leq t_1, t_2 \leq N - 1 \) to construct each \( \Psi_i \), and therefore is such that \( \Psi_i^H \Psi_i = N I_2 \), \( \forall i \in I \). Under this condition, the estimate of channel matrix \( \hat{V}_i \) for the \( i \)-th subblocks can be obtained via the ML principle, or equivalently by means of the least square (LS) technique. That is, we have

\[
\hat{V}_i = (\Psi_i^H \Psi_i)^{-1} \Psi_i^H Y_i = V_i + \frac{1}{N} \Psi_i^H W_i,
\]

where the time- and resource-consuming process to compute the inverse matrix can be avoided.

At the end of the estimation phase, we get \( \hat{g}_{k,i} \) and \( \hat{h}_{k,i} \) for every \( k \) and \( i \), which will be further utilized to acquire estimates of the unknown channel parameters. The following two subsections provide the details of this process.

B. Doppler Shift Estimation

1) Direct Link: Let the acquired channel estimate for the direct BS-UE link \( \hat{g}_{k,i} \) be the sum of \( g_{k,i} \) and its estimation error \( \varepsilon_{k,i} \), and collect \( \{\hat{g}_{k,i}\}_{i=0}^{I-1} \) within each pilot block respectively, yielding

\[
\hat{g}_0 = \beta_1 d_1 + \varepsilon_0,
\]

\[
\hat{g}_1 = \beta_1 \xi_1 d_1 + \varepsilon_1,
\]

where \( \varepsilon_k = [\varepsilon_{k,0}, \ldots, \varepsilon_{k,I-1}]^T \in \mathbb{C}^{I \times 1} \) represents the estimation error vector of \( g_k = [g_{k,0}, \ldots, g_{k,I-1}]^T \), with i.i.d. error \( \varepsilon_{k,i} = \frac{1}{\sqrt{N}} \sqrt{1- \xi} w_{k,i} \sim C\mathcal{N}(0, \frac{2\pi}{N}) \) according to (10), \( \forall k \in K \) and \( \forall i \in I \), \( d_1 = [1, e^{j2\pi f_d T}, \ldots, e^{j2\pi f_d (I-1)T}]^T \in \mathbb{C}^{I \times 1} \) with respect to \( f_{d1} \) is the Doppler-induced phase shift vector for the BS-UE link during block 0, \( \xi_1 \triangleq e^{j2\pi f_d IT} \) denotes the phase shift gap between the two \( i \)-th subblocks of block 0 and block 1, \( \forall i \in I \), and we let \( \alpha_1 \triangleq 2\pi f_{d1} IT \) for ease of exposition.

In order to eliminate the unknown \( \beta_1 \), substitute (11) into (12), and \( \tilde{g}_1 \) can be rewritten as

\[
\tilde{g}_1 = \xi_1 (\hat{g}_0 - \varepsilon_0) + \varepsilon_1 = \xi_1 \hat{g}_0 + \tilde{\varepsilon},
\]

where \( \tilde{\varepsilon} = \varepsilon_1 - \xi_1 \varepsilon_0 \) denotes the composite estimation error vector for the direct link with \( \tilde{\varepsilon} \sim C\mathcal{N}(0, \frac{2\pi}{N} I_2) \). Since \( |\xi_1| = 1 \), we consider the normalized LS (NLS) estimator, developed by further normalizing the amplitude of the corresponding ML or LS estimate. Applying this proposed principle, \( \xi_1 \) can be obtained by

\[
\hat{\xi}_1 = \left\| \hat{g}_0^H \tilde{g}_1 \right\|_2^{-1} \hat{g}_0^H \tilde{\varepsilon},
\]

where we have exploited that the result of inner product \( \hat{g}_0^H \tilde{g}_1 \) is real-valued. Once \( \hat{\xi}_1 \) is obtained, \( f_{d1} \) can be found from

\[
f_{d1} = \frac{\hat{\xi}_1}{2\pi IT}.
\]
2) Cascaded Link: To get the estimates of channel parameters for the cascaded BS-ITS-UE link, we similarly aggregate \( \{h_{k,i}\}_{i=0}^{l-1} \) for each \( k \in K \), i.e.,
\[
\hat{h}_0 = \beta_2 D_2 \Phi a + \zeta_0, \\
\hat{h}_1 = \beta_2 \xi D_2 \Phi a + \zeta_1,
\]
where \( \zeta_k = [\zeta_{k,0}, \ldots, \zeta_{k,l-1}]^T \in C^{I \times 1} \) is the estimation error vector corresponding to \( h_k = [h_{k,0}, \ldots, h_{k,l-1}]^T \) with each i.i.d. error being such that \( \zeta_{k,i} = \frac{1}{\sqrt{\psi}} e^{j\phi_i} w_{k,i} \sim \mathcal{CN}(0, \frac{\sigma^2}{N}) \). \( D_2 = \text{diag} \{e^{j2\pi f IT}, \ldots, e^{j2\pi f (l-1)T}\} \in C^{I \times I} \) with respect to \( f_d \) denotes the Doppler-phase-shift diagonal matrix for the cascaded link, \( \xi \triangleq e^{j\phi_0} \) with its argument \( \alpha_2 \triangleq \frac{2\pi f_d}{T} \) is the phase shift gap for the cascaded link, and \( \Phi = [\Phi_0, \ldots, \Phi_{l-1}]^T \in C^{I \times I} \) is the initial reflection matrix of ITS which can be designed in advance (to be shown in Section III-C.2).

With (16), for the purpose of elimination, \( \hat{h}_1 \) in (17) can be recast as
\[
\hat{h}_1 = \xi (\hat{h}_0 - \zeta_0) + \zeta_1 = \xi \hat{h}_0 + \zeta,
\]
where the composite error vector for the cascaded link \( \zeta = \zeta_1 - \xi \zeta_0 \) is distributed as \( \mathcal{CN}(0, \frac{2\sigma^2}{N} I_1) \). As such, the NLS estimator\(^5\) of \( \xi \) is expressed as
\[
\hat{\xi}_2 = \| \hat{h}_0^H \hat{h}_1 \|_2^{-1} \hat{h}_0^H \hat{h}_1.
\]
Accordingly, \( \hat{f}_d \) is given by
\[
\hat{f}_d = \frac{\hat{\xi}_2}{2\pi IT}.
\]

Remark 2: Since the complex number is a periodic function of its argument with the period \( 2\pi \), it is widely applied that the argument we obtain will be converted into range \((−\pi, \pi]\), i.e., become the result of modulo \( 2\pi \), after utilizing operator \( \angle(\cdot) \). Under this condition, in order to enable the Doppler-shift estimators (15) and (20), we can appropriately set the subblock quantity \( I \) within one block and the subblock duration \( T \) to ensure \( \alpha_1, \alpha_2 \in (-\pi, \pi] \) and thus the modulo nuisance can be circumvented.

Remark 3: Notably, the variance of every channel estimation error \( \varepsilon_{k,i} \) and \( \zeta_{k,i} \) degrades into \( \frac{1}{N} \) noise power as presented above, implying that the growth of \( N \) is beneficial for the accuracy of the channel estimate. However, given the training sequence of fixed length within each block, the increasing \( N \) results in the declining sample amount \( I \) of channel estimates for the direct/cascaded link. To reap the optimal estimation performances of channel parameters using such as (11) and (16), we must consider the design trade-off between \( N \) and \( I \).

C. Path Gain and Phase Difference Estimation

1) Direct Link: With the aid of \( \hat{f}_{d1} \), we can construct the estimate of vector \( \hat{d}_1 \). Consequently, by replacing \( \hat{d}_1 \) with its estimate in (11), the approximated LS estimator of \( \beta_1 \) is expressed as
\[
\hat{\beta}_1 = \frac{1}{T} \hat{d}_1^H \hat{g}_0,
\]
since we have realized that \( \hat{d}_1^H \hat{d}_1 = I 
\]
2) Cascaded Link: Given (16) and (17), we first consider the vertical concatenation of \( \hat{h}_0 \) and \( \hat{h}_1 \), i.e.,
\[
\hat{h} = \beta_2 \Gamma \Phi a + \zeta,
\]
where \( \hat{h} = \begin{bmatrix} \hat{h}_0^T, \hat{h}_1^T \end{bmatrix}^T \in C^{2I \times 1}, \zeta = [\zeta_0^T, \zeta_1^T]^T, \Gamma = \begin{bmatrix} D_2 \ 0_{I \times I} \end{bmatrix} \in C^{2I \times 2I} \) and \( \Phi = \begin{bmatrix} \Phi_0 \ 0_{I \times I} \xi D_2 \end{bmatrix} \in C^{2I \times M} \) denote the Doppler-phase-shift diagonal matrix with respect to \( f_d \) and the initial ITS reflection matrix corresponding to the first two blocks, respectively.

As for the design method of \( \Phi \), similar to that of \( \Psi \) below (9), we preset \( \Phi \) as the submatrix of the \( I \)-th point DFT matrix with its first \( M \) columns for \( I \geq M \), and \( \Phi \) is the vertical combination of \( \Phi \) and its duplicate. Besides, we can obtain the estimate of \( \Gamma \) based on \( \hat{f}_{d2} \). In this case, it is evident that the result of \( \hat{\Gamma} \hat{\Phi} \) is a full-rank thin rectangular matrix, and we have such that \( \hat{\Gamma} \hat{\Phi}^H = 2I_M \). Moreover, let us define \( c \triangleq \beta_2 a \). According to (b) in (5), further conduct the Kronecker product and let \( \beta_2 = \| \beta_2 \|_2 e^{j\phi_2} \), then \( c \) can be rewritten as
\[
c = \| \beta_2 \|_2 e^{j\psi_2}, \tag{23}
\]
where \( z = [\angle \beta_2, \varphi_y, \varphi_z]^T \), and \( \Omega = [I_{M \times 1}, \varpi_y, \varpi_z] \in \mathbb{R}^{M \times 3} \) denotes the non-negative coefficient matrix with the last two columns defined as \( \varpi_y = [0, \ldots, M_y - 1]^T \otimes I_{M_x \times 1} \) and \( \varpi_z = \mathbb{1}_{M_z \times 1} \otimes [0, \ldots, M_z - 1]^T \). This way, we can easily verify the existence of \( \Omega^\dagger \) when \( M_y \geq 2 \) and \( M_z \geq 2 \).

Similar to estimator (21), the approximated LS estimate \( \hat{c} \) using (22) is given by
\[
\hat{c} = \frac{1}{2I} \hat{\Gamma}^H \hat{\Phi}^H \hat{h}. \tag{24}
\]
Based on (23), \( |\beta_2| \) can be obtained from
\[
|\hat{\beta}_2| = \frac{\| \hat{c} \|_1}{M}. \tag{25}
\]
Like \( \alpha_1 \) and \( \alpha_2 \), in order to validate the argument estimation, we assume that the arguments of every entry in \( c \) range within \((-\pi, \pi]\). Then based on (23) again, \( \hat{z} \) can be found from
\[
\hat{z} = \Omega^H \Omega^{-1} \Omega^H \angle \hat{c}. \tag{26}
\]
We emphasize that during the development of the estimators (25) and (26) above, we have considered the estimation errors of each element in \( \hat{c} \) and tried to compensate for them.

In summary, the proposed ML-based closed-form channel estimation algorithm is outlined in Algorithm 1.

Remark 4: Similar to the estimator of \( \beta_2 \), we have found that the vertical concatenation of \( \hat{g}_0 \) and \( \hat{g}_1 \) yields \( \hat{\beta}_1 \). Intuitively, this estimator of \( \beta_1 \) helps to boost the estimation performance compared with its counterpart (21) because of more samples of the channel estimate. Simulations can verify this perception indeed; however, the performance gain of the
Algorithm 1 The ML-Based Closed-Form Channel Estimation Algorithm

Input: Received pilot symbols $y_{k,i,n}$, for all $k$, $i$, $n$, training matrices $\Psi_i^T$, $\forall i$, and initial refraction matrix $\Phi$.

Implementation:
1. Compute $g_{k,i}$ and $h_{k,i}$ using (10), for all $k \in K$, $\forall i \in I$.
2. Obtain $\hat{f}_{z,k}$ based on (14) and (15).
3. Calculate $\hat{f}_{z,0}$ according to (19) and (20).
4. Construct $\beta_i$ using (21).
5. Obtain $\hat{e}$ based on (24).
6. Compute $\hat{\beta}_2$, $\hat{\varphi}_y$ and $\hat{\varphi}_z$ according to (25) and (26).

Output: Doppler shift, path gain and phase difference estimates $\{\hat{f}_{d1}, \hat{f}_{d2}, \hat{\beta}_1, \hat{\beta}_2, \hat{\varphi}_y, \hat{\varphi}_z\}$.

estimation accuracy is relatively small, and the gap from the performance bound, unfortunately, increases.

Remark 5: The pilot requirements for channel estimation are discussed as follows. According to (9), at least two pilots in each subblock are required for the estimation of $\Psi_i$ for all $i \in I$, i.e., $N \geq 2$. Moreover, the subblock quantity within one block has to satisfy such that $I \geq M$ dominantly owing to the design requirement of $\Phi$ below (22). Since we have designed two pilot blocks during one transmission frame, the minimum amount of total training symbols becomes $4M$ in each frame, which depends on the ITS element quantity $M$. Future studies can further economize the pilot overhead, for instance, by using the ITS grouping method proposed in [42] as the result of the high channel spatial correlation.

IV. DERIVATION OF THE CRLBS

This section will derive the CRLBs to evaluate the performances of the proposed channel parameter estimators. The CRLB is a lower bound on the variance of an unbiased estimator and shows the achievable precision of it. The CRLB can also give insight into the effect of various parameters and be useful for design purposes.

A. CLRBs of Doppler Phase and Frequency Shifts

Inspired by the fact that $\hat{f}_{d1}(\hat{f}_{d2})$ has been acquired via the argument of $\hat{\xi}_1(\hat{\xi}_2)$ as previously shown, we will introduce CRLBs in this subsection to bound each estimation variance of these four parameters.

1) Direct Link: We start with the derivation of CRLB for $\hat{\xi}_1$ in detail. With given $\{\xi_1, \hat{g}_0, \varepsilon_0\}$ in (13), the $I$-th dimensional vector $\hat{g}_1$ is conditionally complex Gaussian distributed, and its likelihood function is written as

$$p(\hat{g}_1|\xi_1, \hat{g}_0, \varepsilon_0) = \frac{1}{\det(\pi C_{\hat{g}_1})} e^{-\left(\hat{g}_1 - \mu_{\hat{g}_1}\right)^T C_{\hat{g}_1}^{-1} \left(\hat{g}_1 - \mu_{\hat{g}_1}\right)},$$

(27)

where it is easily shown that

$$\mu_{\hat{g}_1} = E_{\xi_1}[\hat{g}_1] = \xi_1 \hat{g}_0 - \xi_1 \varepsilon_0,$$

(28)

and that

$$C_{\hat{g}_1} = E_{\xi_1}[\left(\hat{g}_1 - \mu_{\hat{g}_1}\right)\left(\hat{g}_1 - \mu_{\hat{g}_1}\right)^T] = \frac{\sigma^2}{N} I.$$

(29)

Introducing the log-likelihood function

$$\Lambda_{\hat{g}_1} = \ln p(\hat{g}_1|\xi_1, \hat{g}_0, \varepsilon_0)$$

$$= -\ln \det(\pi C_{\hat{g}_1}) - (\hat{g}_1 - \mu_{\hat{g}_1})^T C_{\hat{g}_1}^{-1} (\hat{g}_1 - \mu_{\hat{g}_1}).$$

(30)

With (28) and (29), after some tedious manipulations, we further have

$$\Lambda_{\hat{g}_1} = -I \ln \left(\frac{\pi \sigma^2}{N}\right) - \frac{N}{\sigma^2} (\hat{g}_1^H \hat{g}_1 + 2R \{\xi_1 \hat{g}_1^H \varepsilon_0 - \xi_1 \hat{g}_1 H \hat{g}_0\})$$

$$+ |\xi_1|^2 \{\hat{g}_0^H \hat{g}_0 - 2R \{\hat{g}_0^H \varepsilon_0 + \varepsilon_0^H \varepsilon_0\}\}.$$

(31)

Since $\xi_1$ is complex, we suggest to partition its real part and imaginary part, denoted by $\xi_{1,R}$ and $\xi_{1,I}$ respectively, and define the real 2D vector $\xi_1 \equiv [\xi_{1,R}, \xi_{1,I}]^T$. Then, the bound on the variance of $\xi_1$ is given by

$$E[(\xi_1 - \xi_1\hat{)}^T (\xi_1 - \xi_1\hat{)}] \geq \mathcal{F}^{-1}_{\hat{g}_1}(\xi_1),$$

(32)

where $\mathcal{F}_{\hat{g}_1}(\xi_1)$ denotes the Fisher information matrix (FIM) obtained from $\hat{g}_1$ with parameter vector $\xi_1$, which is defined as

$$\mathcal{F}_{\hat{g}_1}(\xi_1) = -E$$

$$\left\{ \begin{array}{c}
\frac{\partial^2 \Lambda_{\hat{g}_1}}{\partial \xi_{1,R}^2} \\
\frac{\partial^2 \Lambda_{\hat{g}_1}}{\partial \xi_{1,I}^2} \\
\frac{\partial^2 \Lambda_{\hat{g}_1}}{\partial \xi_{1,R} \partial \xi_{1,I}} \\
\frac{\partial^2 \Lambda_{\hat{g}_1}}{\partial \xi_{1,I} \partial \xi_{1,R}} \\
\end{array} \right\},$$

(33)

whose both off-diagonal entries are zeros, while diagonal entries are identically given by

$$[\mathcal{F}_{\hat{g}_1}(\xi_1)]_{1,1} = [\mathcal{F}_{\hat{g}_1}(\xi_1)]_{2,2} = \frac{2N}{\sigma^2} \left\{E[H \hat{g}_0^H \hat{g}_0] - 2R \{E[H \hat{g}_0^H \varepsilon_0] + E[H \hat{g}_0^H \varepsilon_0]\}\right\}$$

$$= \frac{2NI}{\sigma^2},$$

(34)

where we have assumed without loss of generality that $|\beta_1| = 1$ (also applied hereafter) for the brevity of exposition, and the statistical expectations have been taken with respect to $\varepsilon_0$. Consequently, the CRLB for the estimation accuracy of $\xi_1$ is expressed as

$$E[(\xi_1 - \xi_1\hat{)}^2] \geq \text{tr} \{[\mathcal{F}^{-1}_{\hat{g}_1}(\xi_1)]\} = \frac{\sigma^2}{NI}.$$

(35)

Moreover, consider the CRLB for $\hat{f}_{d1}$. Since only the argument-related parameter $f_{d1}$ is to be estimated with the unimodular information $|\xi_1| = 1$ known a priori, the corresponding FIM $\mathcal{F}_{\hat{g}_1}(f_{d1})$ degrades to a scalar in this case, and its element is written as

$$-E \left[ \frac{\partial^2 \Lambda_{\hat{g}_1}}{\partial f_{d1}^2} \right] = \frac{8\pi^2 NI T^2}{\sigma^2} R \{E[H \hat{g}_0^H \varepsilon_0] - E[H \hat{g}_0^H \varepsilon_0]\}$$

$$= \frac{8\pi^2 NI T^2}{\sigma^2},$$

(36)

from which we have

$$E[(f_{d1} - \hat{f}_{d1})^2] \geq \mathcal{F}^{-1}_{\hat{g}_1}(f_{d1}) = \frac{\sigma^2}{8\pi^2 NI T^2}. $$

(37)
2) Cascaded Link: Similarly, let us address the bounding problem of \( \xi_2 \) on the estimation performance. Based on (18), the likelihood function of \( \hat{\mathbf{h}}_1 \) with perfectly known \( \{\xi_2, \hat{\mathbf{h}}_0, \xi_0\} \) can be formulated as

\[
p(\hat{\mathbf{h}}_1 | \xi_2, \hat{\mathbf{h}}_0, \xi_0) = \frac{1}{\det(\pi \mathbf{C}_{\hat{\mathbf{h}}_1})} e^{-\frac{1}{2}(\mathbf{h}_1 - \mu_{\hat{\mathbf{h}}_1})^T \mathbf{C}_{\hat{\mathbf{h}}_1}^{-1}(\mathbf{h}_1 - \mu_{\hat{\mathbf{h}}_1})},
\]

where we have that \( \mu_{\hat{\mathbf{h}}_1} = \xi_0 \hat{\mathbf{h}}_0 - \xi_0^2 \mathbf{s}_0 \) and \( \mathbf{C}_{\hat{\mathbf{h}}_1} = \frac{\sigma^2}{N} \mathbf{I}_T \). Consider the log-likelihood function

\[
\Lambda_{\hat{\mathbf{h}}_1} = -I \ln \left( \frac{\sigma^2}{N} \right) - \frac{N}{\sigma^2} (\hat{\mathbf{h}}_1 H \hat{\mathbf{h}}_1 + 2 \mathbf{R} \{\xi_2 \hat{\mathbf{h}}_0^H \mathbf{s}_0 - \xi_0 \hat{\mathbf{h}}_0^H \hat{\mathbf{h}}_0\} - |\xi_2|^2 \{\hat{\mathbf{h}}_0^H \hat{\mathbf{h}}_0 - 2 \mathbf{R} \{\xi_0 \hat{\mathbf{h}}_0^H \mathbf{s}_0 + \xi_0^2 \mathbf{s}_0 \} \}ight).
\]

(39)

Again, since \( \xi_2 \) is complex, it is necessary to define the real 2D vector \( \xi_2 \triangleq [\xi_2^R, \xi_2^I]^T \) containing the real part and imaginary part of \( \xi_2 \), and next construct the FIM as

\[
[\mathbf{F}_{\hat{\mathbf{h}}_1}(\xi_2)]_{p,q} = -E \left[ \frac{\partial^2 \Lambda_{\hat{\mathbf{h}}_1}}{\partial \xi_p \partial \xi_q} \right] \quad \text{ with } 1 \leq p, q \leq 2.
\]

Similar to \( \beta_1 \), we assume \( |\beta_2| = 1 \) hereafter,\(^6\) and hence the aforementioned FIM is succinctly given by

\[
\mathbf{F}_{\hat{\mathbf{h}}_1}(\xi_2) = \begin{bmatrix}
\frac{2NI}{\sigma^2} & 0 \\
0 & \frac{2NI}{\sigma^2}
\end{bmatrix}
\]

(40)

Accordingly, the CRLB on the variance of \( \xi_2 \) holds

\[
E[|\xi_2 - \xi_2|^2] \geq \text{tr} \left( [\mathbf{F}_{\hat{\mathbf{h}}_1}(\xi_2)]^{-1} \right) = \frac{\sigma^2}{NIM}.
\]

(41)

To determine the bound on the estimation performance of \( \hat{\mathbf{f}}_{d2} \), the corresponding scalar FIM is expressed as

\[
[\mathbf{F}_{\hat{\mathbf{f}}_{d2}}(\xi_2)]_{1,1} = -E \left[ \frac{\partial^2 \Lambda_{\hat{\mathbf{f}}_{d2}}}{\partial \xi^2} \right] = \frac{8\pi^2NT^3M^2}{\sigma^2},
\]

(42)

and thus the CRLB for \( \hat{\mathbf{f}}_{d2} \) follows as

\[
E[|\mathbf{f}_{d2} - \mathbf{f}_{d2}|^2] \geq [\mathbf{F}_{\hat{\mathbf{f}}_{d2}}(\xi_2)]_{1,1} = \frac{\sigma^2}{8\pi^2NT^3M^2}.
\]

(43)

B. CRLBs of Path Gains and Phase Differences

1) Direct Link: With the aid of (11), the log-likelihood function of \( \hat{\mathbf{g}}_0 \) conditioned on \( \{\beta_1, \mathbf{d}_1\} \) is written as

\[
\Lambda_{\hat{\mathbf{g}}_0} = -I \ln \left( \frac{\sigma^2}{N} \right) - \frac{N}{\sigma^2} (\hat{\mathbf{g}}_0^H \hat{\mathbf{g}}_0 - 2 \mathbf{R} \{\beta_1 \hat{\mathbf{g}}_0^H \mathbf{d}_1\} + |\beta_1|^2 I).
\]

(44)

Once again, let us separate the real part and imaginary part of complex-valued \( \beta_1 \), denoted by \( \beta_{1,R} \) and \( \beta_{1,I} \) respectively, and construct the 2D real vector \( \beta_1 \triangleq [\beta_{1,R}, \beta_{1,I}]^T \). Accordingly, consider the FIM such that

\[
[\mathbf{F}_{\hat{\mathbf{g}}_0}(\beta_1)]_{p,q} = -E \left[ \frac{\partial^2 \Lambda_{\hat{\mathbf{g}}_0}}{\partial \beta_1^p \partial \beta_1^q} \right] \quad \text{ with } 1 \leq p, q \leq 2.
\]

It is straightforward to realize that the FIM above also has a diagonal structure, with its diagonal entries equally given by

\[
[\mathbf{F}_{\hat{\mathbf{g}}_0}(\beta_1)]_{1,1} = [\mathbf{F}_{\hat{\mathbf{g}}_0}(\beta_1)]_{2,2} = \frac{2NI}{\sigma^2},
\]

(45)

and consequently the CRLB for \( \beta_1 \) is obtained from

\[
E[|\beta_1 - \hat{\beta}_1|^2] \geq \text{tr} \left( [\mathbf{F}_{\hat{\mathbf{g}}_0}(\beta_1)]^{-1} \right) = \frac{\sigma^2}{NI}.
\]

(46)

2) Cascaded Link: Given \( \{\beta_2, \Gamma, \alpha\} \) in (22), the log-likelihood function of \( \hat{\mathbf{h}} \) can be expressed as

\[
\Lambda_{\hat{\mathbf{h}}} = -2I \ln \left( \frac{\sigma^2}{N} \right) - \frac{N}{\sigma^2} (\hat{\mathbf{h}}^H \hat{\mathbf{h}}) - 2R(\beta_2 \hat{\mathbf{h}}^H \Gamma \tilde{\mathbf{a}}) + 2|\beta_2|^2 IM.
\]

(47)

For the case at hand, complex \( \beta_2 \) and real \( \{\varphi_y, \varphi_z\} \) are to be estimated. Let \( \beta_{2,R} \) and \( \beta_{2,I} \) denote the real and imaginary parts of \( \beta_2 \), respectively, and then consider the unknown four-dimensional real vector \( \tilde{z} \triangleq [\beta_{2,R}, \beta_{2,I}, \varphi_y, \varphi_z]^T \). This way, the corresponding FIM is defined as

\[
[\mathbf{F}_{\hat{\mathbf{h}}}(\tilde{z})]_{p,q} = -E \left[ \frac{\partial^2 \Lambda_{\hat{\mathbf{h}}}}{\partial z_p \partial z_q} \right] \quad \text{ with } 1 \leq p, q \leq 4.
\]

Take its \( (1,3) \)th and \( (3,4) \)th elements as examples, which are individually given by

\[
[\mathbf{F}_{\hat{\mathbf{h}}}(\tilde{z})]_{1,3} = -2N \frac{\sigma^2}{\sigma^2} R \left\{ \beta_2 \hat{\mathbf{h}}^H \Gamma \tilde{\mathbf{a}} \right\} \text{ diag} \{\varphi_y, \varphi_z\} \mathbf{a}
\]

(48)

\[
[\mathbf{F}_{\hat{\mathbf{h}}}(\tilde{z})]_{3,4} = 4N \frac{\sigma^2}{\sigma^2} \varphi_y^T \varphi_y.
\]

(49)

Similarly, we can obtain the other entries, and thus the FIM is given by (50), as shown at the bottom of the page. We see that the FIM herein is a real symmetric matrix with a non-diagonal structure, and it is dependant on \( \beta \) and the last two columns of the coefficient matrix \( \Omega \) (i.e., \( \varphi_y \) and \( \varphi_z \)). As a result, we finally determine the bounds as

\[
E[(\tilde{z} - \hat{\tilde{z}})(\tilde{z} - \hat{\tilde{z}})^T] \geq [\mathbf{F}_{\hat{\mathbf{h}}}(\tilde{z})].
\]

(51)

and \( \beta_2 \) is bounded by the summation of the CRLBs for its real and imaginary parts.

V. Numerical Results

This section provides numerical results to assess the performance of the proposed channel estimation algorithm for the ITS-assisted HSR network. The simulation settings are listed as follows. We exploit the mean squared error (MSE) as the performance metric for parameter estimators. The transmit
signal-to-noise ratio (SNR) in dB is defined as $10 \log_{10} \frac{P_s}{N_0}$ as the result of the fixed signal power $P_s = 1$, and we range SNR from 0 to 30 dB with a step of 5 dB. The velocity of the train is set as $v = 100$ m/s, and the carrier wavelength is considered as $\lambda = 0.1$ m (i.e., a 3 GHz carrier frequency), resulting in a Doppler frequency shift with the maximum value of $f_{\text{max}} = \frac{v}{\lambda} = 1$ KHz. Every pilot block includes $I = 40$ subblocks, each further comprising $N = 25$ training pilots, and the subblock duration is set as $T = 0.01$ ms. The path gains for the direct and cascaded links are set as $\beta_1 = e^{j2\pi f_d}$ and $\beta_2 = e^{j2\pi f_d}$, respectively, in order to keep aligned with the assumption $|\beta_1|, |\beta_2| = 1$ for the sake of exposition brevity in Section IV. Finally, the number of ITS elements is fixed to $M = M_y \times M_z = 30$ with varying $M_y$ and $M_z$.

A. Performance Evaluations Using Derived CRLBs

In this subsection, we apply the CRLBs derived in Section IV as accuracy metrics to evaluate the proposed estimators. The Doppler frequency shifts for the direct and cascaded links are fixed to $f_{d1} = 901$ Hz and $f_{d2} = 900$ Hz, respectively. The planar ITS is assumed to comprise $M_y = 5$ columns and $M_z = 6$ rows. The equivalent phase differences of ITS on the $y$ and $z$ axes are set as $\varphi_y = 0.08\pi$ and $\varphi_z = 0.06\pi$, respectively. More than $10^5$ times of Monte-Carlo simulations are run to compute the MSE for each.

We illustrate the MSEs and CRLBs versus SNR for the proposed NLS estimators of $\xi_1$ and $\xi_2$ in Fig. 4. Herein, we also compare the performances of the corresponding non-normalized (NN) (i.e., conventional) LS estimators. We observe that all the MSEs and CRLBs trend downwards with the increasing SNR, as expected. Significantly, our estimators attain their CRLB lower bounds, demonstrating their effectiveness, while constant gaps are found for the NN estimators. Moreover, at the same SNR, the estimation performance of $\hat{\xi}_2$ outperforms its counterpart of $\hat{\xi}_1$. We attribute this to the fact that in contrast to the direct channel, the cascaded channel is superimposed over $M$ propagation paths through the ITS, which enhances the channel and thus protects it from the estimation error.

The MSE and CRLB curves versus SNR for $\hat{f}_{d1}$ and $\hat{f}_{d2}$ are plotted in Fig. 5. We can readily observe that both Doppler-shift estimators have constant but narrow performance gaps from the derived CRLBs. We further observe that this finding follows that of the NN estimators (Fig. 4). This is because our NLS estimators of $\hat{\xi}_1$ and $\hat{\xi}_2$ only enhance the estimation performances of their amplitudes based on the NN estimators, whereas the Doppler estimates are obtained from the corresponding arguments.

In Fig. 6, we depict the MSEs of $\hat{\beta}_1$ and $\hat{\beta}_2$ using proposed estimators with varying SNR. To isolate the effects of Doppler shifts which are acquired in advance, we also estimate the path gains with perfectly known $f_{d1}$ and $f_{d2}$ for comparison, and the performances of which are labeled as idealized MSEs in Fig. 6. We find constant gaps between the MSEs of our estimators and the corresponding CRLBs as opposed to the idealized estimators. We expect this trend since we adopt the estimates of Doppler shifts to extract the path gains, the estimation performances then suffer from error propagation. Fortunately, the estimator of $\hat{\beta}_2$ realizes more estimation potential than that of $\hat{\beta}_1$ with their CRLBs as metrics for the following reasons. First, we can obtain more accurate $\hat{f}_{d2}$ than $\hat{f}_{d1}$ (Fig. 5) before the path gain estimation. Second, we have considered compensating for the left-behind estimation errors during the recovery of $\hat{\beta}_2$ using (25).
The MSE performances of \( \hat{\varphi}_y \) and \( \hat{\varphi}_z \) at different SNRs are illustrated in Fig. 7. We observe that the proposed estimators of the equivalent phase differences reach their CRLBs, unlike the findings from Fig. 6. Herein, readers can verify that each corresponding idealized estimator enables only marginal performance gain with Doppler shifts known a priori. The observations above indicate the effectiveness of the error compensation method applied by our estimator (26). Moreover, the estimator of \( \hat{\varphi}_z \) achieves better performance than that of \( \hat{\varphi}_y \) at the same SNR. This is due to the non-square structure employed at ITS with \( M_z = 6 \) rows and \( M_y = 5 \) columns.

B. Performance Comparisons With Benchmarking Algorithms

This subsection provides simulation comparisons with two benchmarking channel estimation algorithms: the 2D search (2DS) method proposed in [28] (also used in [37]) and the adjacent block estimation (ABE) algorithm proposed in [37]. For comparison fairness, we apply these two algorithms to our proposed transmission scheme (Fig. 3). Specifically, the 2DS method is used for the estimation of \( \{ \hat{f}_{d2}, \hat{\beta}_2, \hat{\varphi}_y \} \) with ULA structure employed at ITS (i.e., let \( M_z = 1 \) and thus omit \( \hat{\varphi}_z \)). The following two steps can conclude the algorithmic process: (i) perform a grid-based exhaustive search to obtain \( \{ \hat{f}_{d2}, \hat{\varphi}_y \} \), and (ii) based on which compute \( \hat{\beta}_2 \). Therefore, a three-dimensional (3D) search is required for the general UPA case, which is rather complicated in practical implementation. Furthermore, the ABE algorithm is designed as the estimators of \( \{ \hat{f}_{d1}, \hat{\beta}_1 \} \), where \( \hat{\beta}_1 \) can be reaped in the same way as our estimator (21) once \( \hat{f}_{d1} \) is recovered. However, in order to get \( \hat{f}_{d1} \), the distinctions from ours exist in: (i) time spacing and (ii) initial-estimate amount. In detail, the ABE method exploits the relation between direct channels for every two adjacent subblocks, and thus the Doppler estimate is the average over \( 2I - 1 \) initial estimates using \( 2I \) subblocks. In comparison, we propose to leverage every two subblocks with time spacing \( IT \) of one block duration rather than subblock duration \( T \), and our Doppler estimate can be regarded as the mean result of only \( I \) initial estimates (see Section III-B).

To ensure fair competition, the 1D ULA framework with \( M_y = 30 \) columns and \( M_z = 1 \) row is identically adopted at ITS for each channel estimation algorithm. In this case, the proposed estimators related to ITS dimension degrade into 1D type, by rewriting (23) as \( e' = [\hat{\varphi}_y] e\Omega^T \) with the new coefficient matrix \( \Omega' = [\mathbf{1}_{M \times 1}, \mathbf{w}_y] \in \mathbb{R}^{M \times 2} \) and \( z' = [\hat{\beta}_2, \varphi_y]^T \) to be estimated. Besides, the proposed estimators of \( \{ \hat{f}_{d1}, \hat{f}_{d2}, \hat{\beta}_1 \} \) keep the same. Moreover, The Doppler shifts \( \hat{f}_{d1} \) and \( \hat{f}_{d2} \) are both uniformly generated from \( U(-f_{\text{max}}, f_{\text{max}}) \). The equivalent phase difference \( \varphi_y \) of ITS is uniformly drawn from \( U(-0.02\pi, 0.02\pi) \). In 2DS implementation, the searching ranges for \( \hat{f}_{d1} \) and \( \varphi_y \) are \( (-f_{\text{max}}, f_{\text{max}}) \) and \( (-\pi, \pi) \), respectively; the uniformly-spaced searching grid on each dimension is adopted with the size of \( S \times S \), and we design that \( S = 700, 1000, \) and \( 1500 \).

We plot the performance comparisons for the estimation of Doppler shifts and path gains in Figs. 8 and 9, respectively. We can see that with the increased searching precision in the 2DS method, the estimation performance of \( \hat{f}_{d2} \) improves and asymptotically approaches that of the proposed estimator at lower SNRs (Fig. 8). We note that the enhanced performance of 2DS is at the cost of more computational consumption and estimation time; our closed-form estimators enable achieving desirable accuracies with low implementation complexity. Besides, we can observe in Fig. 9 that the 2DS method performs worse than ours for the estimation of \( \beta_2 \). This
is expected since \( \{ f_{d2}, \hat{\phi}_y \} \) are applied to the subsequent recovery of \( \beta_2 \), during which the error propagation takes place. Moreover, Fig. 8 and Fig. 9 show that the proposed method outperforms the ABE algorithm for the estimation of both \( f_{d1} \) and \( \beta_1 \), even using less initial Doppler estimates (see the start of this subsection). We attribute this to the fact that longer time spacing (within its upper bound) applied by the estimation of the Doppler shift contributes to boosting the accuracy. Thus, we have carefully designed the block duration \( IT \) as spacing contrary to the subblock duration \( T \) in the ABE method.

VI. CONCLUSION

This paper has contributed to the channel estimation for ITS-assisted HSR wireless networks. We proposed a two-phase transmission scheme where each frame comprises two pilot blocks. Moreover, we modeled the channels with physical parameters and developed a successive, closed-form channel estimation algorithm based on the ML principle and the refraction coefficients of the ITS as prior knowledge. Specifically, we first obtained the channel estimates, from which the channel parameters were recovered by leveraging the relationship between channels for the two pilot blocks. We derived the CRLB for each parameter to evaluate the performance of the corresponding estimator. Numerical results showed the superiority of our algorithm and corroborated the analytical derivations. The challenge for future research or studies will be to utilize our proposed channel estimation algorithm for beamforming design, coding, and other system tasks in order to fully extract the benefits of the emerging ITS technology.

REFERENCES

[1] K. Guan et al., “On millimeter wave and THz mobile radio channel for smart rail mobility,” IEEE Trans. Veh. Technol., vol. 66, no. 7, pp. 5652–5674, Jul. 2017.
[2] B. Ai et al., “Challenges toward wireless communications for high-speed railroad,” IEEE Trans. Intell. Transp. Syst., vol. 15, no. 5, pp. 2143–2158, Oct. 2014.
[3] B. Ai et al., “Future railway services-oriented mobile communications network,” IEEE Commun. Mag., vol. 53, no. 10, pp. 78–85, Oct. 2015.
[4] N. Jamaly, R. Schoch, D. Wenger, and S. Mauron, “Penetration loss into train wagons: Q-factor measurements,” in Proc. 14th Eur. Conf. Antennas Propag. (EuCAP), Mar. 2020, pp. 1–5.
[5] G. I. Kiani, L. G. Olsson, A. Karlsson, K. P. Esselle, and M. Nilsson, “Cross-dipole bandpass frequency selective surface for energy-saving glass used in buildings,” IEEE Trans. Antennas Propag., vol. 59, no. 2, pp. 520–525, Feb. 2011.
[6] N. Jamaly, D. Scanterla, C. Genoud, and H. Lehmann, “Analysis and measurement of penetration loss for train wagons with coated vs uncoated windows,” in Proc. 27th Eur. Conf. Antennas Propag. (EuCAP), Apr. 2018, pp. 1–5.
[7] G. Yang, J. Du, and M. Xiao, “Maximum throughput path selection with random blockage for indoor 60 GHz relay networks,” IEEE Trans. Commun., vol. 63, no. 10, pp. 3511–3524, Oct. 2015.
[8] V. Raghavan et al., “Millimeter-wave MIMO prototype: Measurement and experimental results,” IEEE Commun. Mag., vol. 56, no. 1, pp. 202–209, Jan. 2018.
[9] B. Ai, A. F. Molisch, M. Rupp, and Z. Zhong, “5G key technologies for smart railways,” Proc. IEEE, vol. 108, no. 6, pp. 856–893, Jun. 2020.
[10] Q. Wu and R. Zhang, “Towards smart and reconfigurable environment: Intelligent reflecting surface aidied wireless network,” IEEE Commun. Mag., vol. 58, no. 1, pp. 106–112, Jan. 2020.
[11] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M. Alouini, and R. Zhang, “Wireless communications through reconfigurable intelligent surfaces,” IEEE Access, vol. 7, pp. 116753–116773, 2019.
[12] Y. Liu et al., “Reconfigurable intelligent surfaces: Principles and opportunities,” IEEE Commun. Surveys Tuts., vol. 23, no. 3, pp. 1546–1577, 3rd Quart., 2021.
[13] Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming,” IEEE Trans. Wireless Commun., vol. 18, no. 11, pp. 5394–5409, Nov. 2019.
[14] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, “Intelligent reflecting surface-aided wireless communications: A tutorial,” IEEE Trans. Commun., vol. 69, no. 5, pp. 3313–3351, May 2021.
[15] T. Hou, Y. Liu, Z. Song, X. Sun, Y. Chen, and L. Hanzo, “Reconfigurable intelligent surface aided NOMA networks,” IEEE J. Sel. Areas Commun., vol. 38, no. 11, pp. 2575–2588, Nov. 2020.
[16] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, “Reconfigurable intelligent surfaces for energy efficiency in wireless communication,” IEEE Trans. Wireless Commun., vol. 18, no. 8, pp. 4157–4170, Aug. 2019.
[17] C. Huang, R. Mo, and C. Yuen, “Reconfigurable intelligent surface assisted multiuser MISO systems exploiting deep reinforcement learning,” IEEE J. Sel. Areas Commun., vol. 38, no. 8, pp. 1839–1850, Aug. 2020.
[18] M. Di Renzo et al., “Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and the road ahead,” IEEE J. Sel. Areas Commun., vol. 38, no. 11, pp. 2450–2525, Nov. 2020.
[19] Q. Wu and R. Zhang, “Beamforming optimization for wireless network aided by intelligent reflecting surface with discrete phase shifts,” IEEE Trans. Commun., vol. 68, no. 3, pp. 1838–1851, Mar. 2020.
[20] R. Li, B. Guo, M. Tao, Y.-F. Liu, and W. Yu, “Joint design of hybrid beamforming and reflection coefficients in RIS-aided mmWave MIMO systems,” IEEE Trans. Commun., vol. 70, no. 4, pp. 2404–2416, Apr. 2022.
[21] E. Basar, “Reconfigurable intelligent surfaces for Doppler effect and multipath fading mitigation,” 2019, arXiv:1912.04809.
[22] K. Wang, C.-T. Lam, and B. K. Ng, “IRS-aided predictable high-mobility vehicular communication with Doppler effect mitigation,” in Proc. IEEE 93rd Veh. Technol. Conf. (VTC-Spring), Apr. 2021, pp. 1–6.
[23] C. Xu et al., “Channel estimation for reconfigurable intelligent surface assisted high-mobility wireless systems,” IEEE Trans. Veh. Technol., vol. 72, no. 1, pp. 718–734, Jan. 2023.
[24] K. Wang, C.-T. Lam, and B. K. Ng, “RIS-aided high-speed communications with time-varying distance-dependent Rician channels,” Appl. Sci., vol. 12, no. 22, p. 11857, Nov. 2022.
[25] C. Xu et al., “Reconfigurable intelligent surface assisted multi-carrier wireless systems for doubly selective high-mobility Ricean channels,” IEEE Trans. Veh. Technol., vol. 71, no. 4, pp. 4023–4041, Apr. 2022.
[26] Y. Wang, G. Wang, R. Xu, R. He, B. Ai, and H. Xiao, “Joint channel estimation and data detection for intelligent transparent surface (ITS) aided wireless communications on railways,” in Proc. 13th Int. Conf. Wireless Commun. Signal Process. (WCSP), Oct. 2021, pp. 1–5.
[27] J. Lin, G. Wang, R. Xu, and H. Xiao, “Channel and phase shift estimation for TM-aided OTFS railway communications,” in Proc. IEEE/CIC Int. Conf. Commun. China (ICCC Workshops), Jul. 2021, pp. 444–448.
[28] Z. Huang, B. Zheng, and R. Zhang, “Transforming channel from fast to slow: IRS-aided high-mobility communication,” in Proc. IEEE Int. Conf. Commun., Jun. 2021, pp. 1–6.
[29] Z. Huang, B. Zheng, and R. Zhang, “Transforming channel from fast to slow: Intelligent reflecting surface aided high-mobility communication,” IEEE Trans. Wireless Commun., vol. 21, no. 7, pp. 4989–5003, Jul. 2022.
[30] H. Zhang, B. Di, K. Bian, Z. Han, H. V. Poor, and L. Song, “Toward ubiquitous sensing and localization with reconfigurable intelligent surfaces,” Proc. IEEE, vol. 110, no. 9, pp. 1401–1422, Sep. 2022.
[31] C. Huang et al., “Holographic MIMO surfaces for 6G wireless networks: Opportunities, challenges, and trends,” IEEE Wireless Commun., vol. 27, no. 5, pp. 118–125, Oct. 2020.
[32] A. Arbab, Y. Horie, M. Bagheri, and A. Farao, “Dielectric metasurfaces for complete control of phase and polarization with subwavelength spatial resolution and high transmission,” Nature Nanotechnol., vol. 10, no. 11, pp. 937–943, Nov. 2015.
[33] Y. F. Yu, A. Y. Zhu, R. Paniagua-Dominguez, Y. H. Fu, B. Luk’yanchuk, and A. I. Kuznetsov, “High-transmission dielectric metasurface with 2π phase control at visible wavelengths,” Laser Photon. Rev., vol. 9, no. 4, pp. 412–418, Jun. 2015.
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