Orthogonal Spatial Domain Subspace Projection Based Time-Varying Channel Estimation

RONG ZENG\(^{1,2}\), QIANG HUANG\(^1\), AND HAO WANG\(^1\), (Member, IEEE)

\(^1\)School of Communications Engineering, Hangzhou Dianzi University, Hangzhou 310018, China
\(^2\)National Mobile Communications Research Laboratory, Southeast University, Nanjing 210096, China

Corresponding author: Rong Zeng (zengrong@hdu.edu.cn)

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ABSTRACT Time-varying channel estimation is a well-known challenge for the wireless communications in the high mobility environments. In this paper, we propose a basis expansion model (BEM) based channel estimation algorithm utilizing orthogonal spatial domain subspace projection. The channel estimation is taken on each subspace and the estimation results of all subspaces are combined to obtain the final time-varying channel parameters. In our proposed scheme, the wave number spectrum shifting is utilized to suppress the time-varying level on each subspace and the wave number spectrum recovery is adopted in the combination process. Simulation results are provided to verify our proposed scheme.

INDEX TERMS Time-varying channel estimation, high mobility environments, orthogonal spatial domain subspace projection.

I. INTRODUCTION

Due to the large-scale deployment of high speed railway (HSR) systems and the increasing popularity of highway vehicle communication systems, wireless communication in high mobility environments has recently attracted considerable attention [1]–[4]. High mobility has been incorporated as one of the key features of the sixth generation (6G) communications [5]. The orthogonal frequency division multiplexing (OFDM) has become a dominant technique due to its robustness to frequency-selective channels and high spectral efficiency. One of the main challenges for OFDM systems in high mobility communications is the time-varying channel estimation [6], [7].

There exist three types of estimation algorithms to extract the time-varying fading channel parameters [8]. The interpolation based method adopts interpolation on the adjacent known channel parameters locations, where the interpolation weights are set based on the Doppler effect and the time-domain channel correlations. In [9], the bit error rate (BER) floor performance of 16-QAM OFDM signal was studied when the polynomial interpolation based channel estimation is adopted. A 2D complex Support Vector Machine Regression (SVR) algorithm based on the Radial Basis Function (RBF) kernel was proposed in [10], which performs simultaneous interpolation in frequency and time domains.

The performance of the interpolation method degrades rapidly with the channel Doppler spread increasing, which is due to the high level modeling error.

In addition, the Gaussian-Markov models are also utilized to track the time-varying channel through symbol-by-symbol updating. In [11], an advanced finite-state Markov chain (FSMC) channel model for HSR was proposed, which incorporates the impacts of moving speed on the temporal channel statistical characteristic. And the channel states are defined based on the signal to noise ratios (SNRs) via the equal step-size partitioning method. In [12], the ternary Markov channel (TMC) was proposed to characterize the ternary discrete channels with memory and soft-information, which generalizes the Gilbert–Elliott channel (GEC) in the sense that each binary symmetric channel (BSC) is replaced by a discrete memoryless channel with binary input and ternary output.

The basis expansion model (BEM) is widely used to characterize the time-varying channel recently by utilizing the basis functions scaled with corresponding coefficients. The time-varying channel estimation is converted into the estimation of the basis coefficients [13], [14]. In [15], the choice for the dimensionality of the BEM and the bandwidth of frequency-domain channel estimation were investigated, which have significant impact on the quality of channel estimation and the complexity of signal processing algorithms. A BEM based on the maximum likelihood (ML) criteria was adopted to model the combined phase-noise, nonlinearities, and self-interference channel coefficients [16].
In [17], a two-dimensional BEM was proposed to estimate the channel expansion, which depends on the maximum delay spread and maximum Doppler spread. In [18], the compressed sensing was used in the channel estimation utilizing the channel sparsity and the inter-carrier interference is eliminated by exploiting the location information of trains. A pilot pattern design scheme was proposed to reduce the system coherence and improve the compressed sensing based channel estimation accuracy. The BEM channel estimation algorithms are still susceptible to the moving speed and channel model mismatch. In this paper, we address the problem of time-varying channel estimation in high mobility environments. A proper channel estimator special for high mobility should maintain robust performance under fast changing communication environments. In order to meet this requirements, we propose an orthogonal spatial domain subspace projection based time-varying channel estimation algorithm.

Moreover, in this paper, we mainly consider the application scenarios where the base stations and reflectors are normally static or with low mobility, such as HSR and Vehicle-To-Network (V2N), Vehicle-To-Infrastructure (V2I), Vehicle-To-Pedestrian (V2P) in Vehicle-To-Everything (V2x).

As for Vehicle-To-Vehicle (V2V), where the transmitter, receiver and reflectors are all in high mobility, the Doppler shift and frequency offset joint estimation and compensation can be taken on each subspace respectively after the orthogonal subspace projection and the wave number spectrum shifting process.

The remainder of this paper is organized as follows. Section II introduces system model. In Section III, a novel BEM based channel estimator with orthogonal spatial domain subspace projection is proposed for high mobility environments. The simulation results are presented in Section IV. Finally, Section V concludes this paper.

II. SYSTEM MODEL

Focusing the scenario we studied, the Doppler effect is mainly induced by the movement of the mobile stations. The transmitted signal spreads through multipath channel, which is induced by the various reflectors around the moving user equipment (UE), such as buildings and mountains. The time-varying multipath channel response can be modeled as

\[
h(n) = \sum_{l=0}^{L-1} \alpha_l a(\theta_l, \varphi_l)^T \delta(n - \tau_l) \\
\times \exp(j2\pi nf_d T_s (\sin\varphi_l \sin \psi \cos(\theta_l - \vartheta) \\
+ \cos\varphi_l \cos \psi)),
\]

where \( L \) is the total number of resolvable multipaths, \( f_d \) is the maximal Doppler frequency, \( \tau_l \) is the relative delay of the \( l \)-th path, \( \theta_l \) is the angle between the \( l \)-th path incident signal projection direction to X-Y plane and X axis, \( \varphi_l \) is the angle between the \( l \)-th path incident signal and Z axis, \( \psi \) is the angle between the projection direction of moving to X-Y plane and X axis, \( \vartheta \) is the angle between the moving direction and Z axis,

\( \alpha_l \) is the scattering coefficient of the \( l \)-th path, \( a(\theta_l, \varphi_l)^T \) is the transpose vector of \( a(\theta_l, \varphi_l) \), \( a(\theta_l, \varphi_l) \) is the array response vector at receiver of the \( l \)-th path. As for UCA (Uniform Circle Array) shown in Fig. 1[19],

\[
a(\theta_l, \varphi_l) = \begin{bmatrix}
\frac{\sin \theta_l \cos(-\varphi_l)/c}{c} \\
\frac{\cos\theta_l \cos(2\pi n f_d T_s - \varphi_l)/c}{c} \\
\vdots \\
\frac{\sin \theta_{N_c} \cos(-\varphi_l)/c}{c}
\end{bmatrix}^T,
\]

where \( \omega, c, R, n_f \) is the carrier angular frequency, speed of light, radius of antenna array and the number of antennas at receiver, respectively.

In this paper, we consider the OFDM system with \( N_c \) subcarriers, where each frame has \( N_b \) OFDM blocks. Let \( X_b = [X_b(0), X_b(1), \ldots, X_b(N_c - 1)] \) represents the information symbols in the \( b \)-th OFDM block, then the \( N_c \) point inverse discrete Fourier transform (IDFT) is applied and the cyclic prefix (CP) is added to each block. The time-domain sample in the \( b \)-th block is given by

\[
x_b(n) = \frac{1}{\sqrt{N_c}} \sum_{k=0}^{N_c-1} X_b(k) e^{j2\pi nk/N_c}, \quad -N_{cp} \leq n \leq N_c - 1,
\]

where \( N_{cp} \) is the length of the CP. Then the time-domain transmitted signal can be expressed as \( x(n) = \sum_{b=0}^{N_c-1} x_b(n - bN_s) \), where \( N_s = N_c + N_{cp} \).

The received signal through the time-varying multipath channel is given by

\[
y(n) = \sum_{l=0}^{L-1} \alpha_l a(\theta_l, \varphi_l)^T \tilde{x}(n - \tau_l) \\
\times \exp(j2\pi nf_d T_s (\sin\varphi_l \sin \psi \cos(\theta_l - \vartheta) \\
+ \cos\varphi_l \cos \psi)) + z(n),
\]
where \( z(n) \) is the additive white Gaussian noise (AWGN) vector.

### III. BASIS EXPANSION MODEL BASED ORTHOGONAL SPATIAL DOMAIN SUBSPACE PROJECTION CHANNEL ESTIMATION

In this paper, we use the orthogonal spatial domain subspace projection to project the signals into mutually orthogonal subspaces. In each subspace, the signal wave number spectrum is shifted to the zero wave number point around. The root mean square wave number spread is suppressed through subspace projection. The wave number spectrum shifting is adopted to reduce the wave number mean value of each subspace signal and the time-varying level of equivalent channel parameters is attenuated. The BEM-based channel estimation is performed in each subspace separately. The equivalent channel estimation results in each subspace are re-shifted to the corresponding wave number positions. Finally, the final channel estimation is obtained by combining all the equivalent channel estimation results after wave number spectrum recovery.

#### A. ORTHOGONAL SPATIAL DOMAIN SUBSPACE PROJECTION

In the receiver, the orthogonal spatial domain subspace projection is utilized to divide the received signal into different wave number scopes. The UCA is implemented at the receiver, and the spatial filter vector can be define as

\[
e_r(\beta, \gamma) = \frac{1}{\sqrt{\nu_r}} \left[ \exp \left( -j \omega R_n \sin \beta \cos (-\gamma) \right) \right. \\
\left. \exp \left( -j \omega R_n \sin \beta \cos \left( \frac{2\pi}{\nu_r} - \gamma \right) \right) \right],
\]

where \( \beta \) is the angle between the subspace beam direction and Z axis, and \( \gamma \) is the angle between the subspace beam direction and X axis.

Define the matrix \( \mathbf{U}_r \) as

\[
\mathbf{U}_r = \begin{bmatrix} \mathbf{U}_r^0 & \mathbf{U}_r^1 & \cdots & \mathbf{U}_r^{\nu_r-1} \end{bmatrix},
\]

where

\[
\mathbf{U}_r^k = \begin{bmatrix} \mathbf{e}_r(\beta_k, \gamma_0) & \mathbf{e}_r(\beta_k, \gamma_1) & \cdots & \mathbf{e}_r(\beta_k, \gamma_{\nu_r-1}) \end{bmatrix}.
\]

The received signals projected to the orthogonal subspaces are

\[
y_a(n) = \mathbf{U}_r^T \tilde{y}(n),
\]

where \( \tilde{y}(n) \) is a \( n_r^2 \times 1 \) vector and can be expressed as

\[
y_a(n) = \begin{bmatrix} y_a^0(n) & y_a^1(n) & \cdots & y_a^{\nu_r^2-1}(n) \end{bmatrix}^T.
\]

Then the wave number spectrum shifting is implemented as

\[
\tilde{y}_a(n) = \tilde{y}_a(n) \circ \mathbf{P}(n),
\]

where \( \circ \) represents the Hadamard product, and the Doppler shift pre-compensation vector \( \mathbf{P}(n) \) in (12), as shown at the bottom of this page,

\[
\mathbf{P}(n) = \begin{bmatrix} p_0(n) & p_1(n) & \cdots & p_{\nu_r-1}(n) \end{bmatrix}^T.
\]

The combined wave number spectrum shifted signal \( \tilde{y}_a(n) \) can be expressed as

\[
\tilde{y}_a(n) = \begin{bmatrix} 1 & 1 & \cdots & 1 \end{bmatrix}_{1 \times \nu_r^2} \tilde{y}_a(n)
\]

\[
= \sum_{l=0}^{L-1} \tilde{h}_{a,l}(n) \tilde{x}(n - \tau_l) + \tilde{z}(n),
\]

when \( |\psi_l - \beta_l| \leq \frac{\pi}{2\nu_r} \) and \( |\theta_l - \gamma_l| \leq \frac{\pi}{\nu_r} \) are satisfied, then the wave number spectrum shifted equivalent channel parameters can be expressed in (14), as shown at the bottom of this page.

#### B. CHANNEL ESTIMATION

The discrete-time BEM channel model can be expressed as

\[
h_l(n) = \sum_{q=-Q}^{Q} \varepsilon_{l,q} \zeta_q(n),
\]

where \( Q \) is the order of BEM, \( \varepsilon_{l,q} \) is the corresponding basis coefficient of the \( l \)-th path for the \( q \)-th basis function \( \zeta_q \). As for Complex Exponential BEM (CE-BEM) [20],

\[
\zeta_q(n) = \exp^{2\pi inq/gN_c},
\]

where \( g \) is a nonzero integer determined by the sampling resolution in the Doppler frequency domain.

The wave number spectrum shifted equivalent channel parameters on \( k \)-th subspace are

\[
\tilde{h}_{a,l}(n) = \sum_{q=-Q}^{Q} \tilde{e}_{l,q}^{k} \zeta_q(n).
\]

The combined wave number spectrum shifted signal \( \tilde{y}_a(n) \) can be expressed as

\[
y_a(n) = \mathbf{U}_r^T \tilde{y}(n),
\]

where \( \tilde{y}(n) \) is a \( n_r^2 \times 1 \) vector and can be expressed as

\[
y_a(n) = \begin{bmatrix} y_a^0(n) & y_a^1(n) & \cdots & y_a^{\nu_r^2-1}(n) \end{bmatrix}^T.
\]

Then the wave number spectrum shifting is implemented as

\[
\tilde{y}_a(n) = \tilde{y}_a(n) \circ \mathbf{P}(n),
\]

where \( \circ \) represents the Hadamard product, and the Doppler shift pre-compensation vector \( \mathbf{P}(n) \) in (12), as shown at the bottom of this page,

\[
\mathbf{P}(n) = \begin{bmatrix} p_0(n) & p_1(n) & \cdots & p_{\nu_r-1}(n) \end{bmatrix}^T.
\]

The combined wave number spectrum shifted signal \( \tilde{y}_a(n) \) can be expressed as

\[
\tilde{y}_a(n) = \begin{bmatrix} 1 & 1 & \cdots & 1 \end{bmatrix}_{1 \times \nu_r^2} \tilde{y}_a(n)
\]

\[
= \sum_{l=0}^{L-1} \tilde{h}_{a,l}(n) \tilde{x}(n - \tau_l) + \tilde{z}(n),
\]

when \( |\psi_l - \beta_l| \leq \frac{\pi}{2\nu_r} \) and \( |\theta_l - \gamma_l| \leq \frac{\pi}{\nu_r} \) are satisfied, then the wave number spectrum shifted equivalent channel parameters can be expressed in (14), as shown at the bottom of this page.
The received signals projected into the $k$-th subspace can be written as
\[
\tilde{y}_a^k(n) = \sum_{q=-Q}^{Q} \xi_q(n) \sum_{l=0}^{L-1} \tilde{e}_{l,q}^k(n - \tau_l) + z'(n),
\] (18)

The time-varying channel parameters estimation becomes the estimation of the BEM basis coefficients $\tilde{e}_{l,q}^k$.

The receive signals in the $k$-th subspace can also be written as
\[
\tilde{y}_a^k = \sum_{q=-Q}^{Q} G_q C(\tilde{x}) \varepsilon^k_q + z',
\] (19)

where
\[
G_q = \text{diag}[\xi_q(0) \xi_q(1) \cdots \xi_q(N_c - 1)].
\] (20)

$C(\tilde{x})$ is a matrix with $L$ columns of circularly shifted $\tilde{x}$,
\[
C(\tilde{x}) = \begin{bmatrix}
\tilde{x}(0) & \tilde{x}(N_c - 1) & \cdots & \tilde{x}(N_c - L + 1) \\
\tilde{x}(1) & \tilde{x}(0) & \cdots & \tilde{x}(N_c - L + 2) \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{x}(N_c - 1) & \tilde{x}(N_c - 2) & \cdots & \tilde{x}(N_c - L)
\end{bmatrix},
\] (21)

and
\[
\varepsilon^k_q = \begin{bmatrix}
\tilde{z}_{0,q}^k & \tilde{e}_{1,q}^k & \cdots & \tilde{e}_{L-1,q}^k
\end{bmatrix}^T,
\] (22)

and form the augmented matrix
\[
M = \begin{bmatrix}
G_{-Q} C(\tilde{x}) & G_{-Q+1} C(\tilde{x}) & \cdots & G_Q C(\tilde{x})
\end{bmatrix},
\] (23)

and
\[
E^k = \begin{bmatrix}
(\varepsilon_{-Q}^k)^T & (\varepsilon_{-Q+1}^k)^T & \cdots & (\varepsilon_Q^k)^T
\end{bmatrix}^T,
\] (24)

then
\[
\tilde{y}_a^k = ME^k + z'.
\] (25)

We use the frequency domain pilot pattern, $B = F^H M$, $F$ is the IFFT matrix, then
\[
B = B_p + B_d,
\] (26)

where $B_p$ contains the pilot symbols, $B_d$ contains the data symbols. Then
\[
\tilde{y}_{a,F}^k = B_p E^k + B_d E^k + z'_F.
\] (27)

Let $s$ includes all the symbols where pilots are mounted, the Least Square (LS) estimation of the BEM coefficients $E^k$ in the $k$-th subspace is given by
\[
\hat{E}_{LS}^k = E^k + B_p(s,:) + \sum_{k} \left[ B_d(s,:) E^k + z'_F(s,:) \right],
\] (28)

where $B^+ = (B^H B)^{-1} B^H$ is the Moor-Penrose pseudo inverse of $B$.

Restructure the equivalent channel basis coefficients matrix as
\[
\tilde{E}_{LS}^k = \begin{bmatrix}
\hat{E}_{LS}^k(1) & \hat{E}_{LS}^k(2) & \cdots & \hat{E}_{LS}^k(2QL + 1) \\
\hat{E}_{LS}^k(2) & \hat{E}_{LS}^k(3) & \cdots & \hat{E}_{LS}^k(2QL + 2) \\
\vdots & \vdots & \ddots & \vdots \\
\hat{E}_{LS}^k(L) & \hat{E}_{LS}^k(2L) & \cdots & \hat{E}_{LS}^k((2Q + 1)L)
\end{bmatrix}_{L \times (2Q + 1)}
\] (29)

where $\hat{E}_{LS}^k(n)$ represents the $n$-th element of vector $\hat{E}_{LS}^k$. And the channel impulse response in the $k$-th subspace can be written as
\[
\hat{H}_{LS}^k = \hat{E}_{LS}^k \Delta,
\] (30)
where $\Delta = [\xi_0 \xi_1 \cdots \xi_{Q-1}]^T$ and $\xi_q = [\xi_q(0) \xi_q(1) \cdots \xi_q(N_c-1)]^T$.

Define the Doppler recovery vector in (31), as shown at the bottom of this page.

Then the channel Doppler response in the $k$-th subspace after wave number spectrum recovery can be expressed as

$$\hat{H}_k = \tilde{H}_{k,LS} \circ \left( \begin{array}{c} 1 \\ 1 \\ \vdots \\ 1 \end{array} \right)_{L \times 1}.$$  \hspace{1cm} (32)

Finally, the channel impulse response estimations in each orthogonal subspace are combined to obtain the final channel impulse response estimation as

$$\hat{H} = \sum_{k=0}^{L-1} \hat{H}_k.$$  \hspace{1cm} (33)

As for the computational complexity of our proposed scheme, because each element in projection matrix $U_r$ is complex exponential function with unit module, this projection process can be implemented with hardware analog phase shifter or digital phase shifter. Therefore, this projection process will not increase the burden of digital signal processor. Moreover, the Moor-Penrose pseudo inverse of $B_p(s, :)$ is unrelated with the received signal and subspace index, which means that the Moor-Penrose pseudo inverse of $B_p(s, :)$ is the same for every subspace and can be calculated offline. These factors will alleviate the real-time computational burden on the digital signal processor.

### IV. SIMULATION RESULTS

In this section, simulation results are presented to illustrate the performance of the proposed channel estimation scheme in OFDM systems. The normalized mean squared error (NMSE) is adopted to evaluate the performance, which is

$$\text{NMSE} = E \left[ \frac{\|H - \hat{H}\|^2}{\|H\|^2} \right].$$  \hspace{1cm} (34)

In the simulation, the time-frequency double selective fading channel with resolvable multipaths $L = 2$ is utilized. The uniform circular array is adopted at the receiver side. The simulation conditions are: the carrier frequency is 2 GHz, $N_c = 1024$, movement speed is 300 km/h, and symbol period is 5 $\mu$s.

In Fig.2, we compare the channel impulse response before and after the wave number spectrum shifting. In the simulation, the real part and imaginary part of the equivalent channel coefficients on each subspace are presented. Re($B$) means the real part of the equivalent channel coefficients before the wave number spectrum shifting. Im($A$) means the imaginary part of the equivalent channel coefficients after the wave number spectrum shifting. It is obvious that the time-varying level of the equivalent channel coefficients after the wave number spectrum shifting is much smaller than that before the wave number spectrum shifting.

For comparison, we also provide the performance of the traditional BEM-LS estimator. In the simulation results, the parameter ‘PW’ means the pilot width, which refers to the number of pilot symbols in each pilot group [21]. The horizontal axis of the simulation results is SNR,$n_r$. It means that for the same SNR,$n_r$ value and wireless propagation conditions, the transmit power of multi-antenna system is much lower than that of single antenna system. Moreover, in most of the high mobility scenarios(such as HSR and V2x), the distance between the receiver and the transmitter is relatively short. It means the higher working SNR can be assumed in these scenarios. Fig.3 compares the channel estimation NMSE of proposed scheme based on spatial domain subspace projection(Pro.) and the BEM-LS with different PW and $n_r$. As can be observed from the simulations, the performance of our proposed scheme is much better than BEM-LS. The main reason is that our proposed scheme adopts the wave number spectrum shifting.
In the three-dimensional coordinate system shown in Fig. 1, DOPPLER ANGLE CALCULATION channel estimation algorithm BEM-LS. under high mobility environments and obtain better channel scheme. This estimator can well solve the Doppler effect subspace projection based time-varying channel estimation. In this paper, we proposed an orthogonal spatial domain effectively suppressed.

V. CONCLUSION
In this paper, we proposed an orthogonal spatial domain subspace projection based time-varying channel estimation scheme. This estimator can well solve the Doppler effect and the direction of moving can be calculated in (37), as shown at the top of this page.

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RONG ZENG was born in Jiangsu, China, in 1976. He received the Ph.D. degree in electrical engineering from Southeast University, Nanjing, China, in 2004. From 2004 to 2006, he was a System and Algorithm Engineer with COMMIT, Inc., Shanghai, China. From 2015 to 2016, he was a Visiting Scholar with the Department of Electrical and Computer Engineering, Colorado State University, Fort Collins, CO, USA. He is currently an Associate Professor with the School of Communication Engineering, Hangzhou Dianzi University, Hangzhou, China. His research interests include 5G/6G wireless systems, the Internet of Things (IoT), and V2X.
QIANG HUANG was born in Jiangxi, China, in 1995. He received the M.S. degree in communication engineering from Hangzhou Dianzi University, Hangzhou, China, in 2020. His research interests include wireless access technology and V2X.

HAO WANG (Member, IEEE) was born in Anhui, China, in 1985. He graduated from Huangshan University, China, in 2005. He received the M.S. degree from the Anhui University of Technology, China, in 2010, and the Ph.D. degree from Southeast University, China, in 2014. He is currently with the School of Communication Engineering, Hangzhou Dianzi University. His current research interests include low-complexity finite impulse response (FIR) filter design and digital image correlation method.

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