Novel Algorithm for Prediction of Wideband Mobile MIMO Wireless Channels

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***Abstract*—We investigate the prediction of wideband MIMO spatial channels. We propose a two-stage long range parametric prediction scheme that exploits the temporal, spatial and frequency correlations in a realistic cluster based fading channel. The proposed scheme utilizes the frequency correlation in an ESPRIT-like approach to estimate the cluster delays and scattering coefficients. The spatial and temporal correlations are then used to jointly estimate the angles of arrival, angles of departure and Doppler shifts via a 3D ESPRIT algorithm. Simulation results using the standardized 3GPP/WINNER II spatial channel model show that the proposed algorithm offers improved prediction performance over previous methods and can achieve longer prediction range.**

***Index Terms*—MIMO-OFDM, multipath propagation, cluster based models, estimation and prediction, ESPRIT**

I. Introduction

The performance of MIMO-OFDM systems is limited by multipath fading - temporal and frequency variations of the channel induced by multipath propagation and mobility in the scattering medium. The variation of the received signal power resulting from channel fading can potentially result in loss of transmission and degrades the overall system performance. Adaptive MIMO-OFDM wireless systems overcome this limitation by varying the transmit power, modulation scheme and/or order, and coding for each subcarrier based on the currently available channel state information (CSI) at the transmitter [1, 2]. Transmit side CSI is typically obtained in time division duplex systems by using reciprocity of the forward and reverse channels. However, in frequency division duplex systems, CSI is obtained at the receiver and fedback to the transmitter via a dedicated low rate feedback link. Because of the inherent processing and feedback delay, the CSI rapidly becomes outdated before its actual usage for link adaptation at the transmitter, particularly in high mobility scenarios.

Prediction of future channel states has been studied and shown to be efficient in mitigating performance degradation resulting from outdated CSI [3–8]. The potential of utilizing the additional information resulting from multiple sampling of the wavefield in the prediction of MIMO-OFDM channel was illustrated in [9, 10]. The authors showed using the Cramer-Rao bound that significant improvement in prediction error and achievable prediction horizon can be achieved from using the additional spatial dimension in MIMO channels. There is, however, no prediction algorithm in the open literature to the best knowledge of the authors, that fully exploit this additional information.

Motivated by the benefits of channel prediction for enabling adaptive transmission in mobile MIMO-OFDM systems and the gain offered by using the spatial structure of the MIMO channel to aid prediction, we here investigate parametric channel prediction using subspace based parameter estimation. We utilize a far-field cluster based double directional spatial channel model (SCM) for MIMO systems as obtained in recent standardized MIMO channel models such as 3GPP/WINNER II [11] and COST273 [12]. We propose a 2 stage ESPRIT based parameter estimation algorithm comprising of 1-dimensional cluster parameter estimation stage followed by 3-dimensional joint angle of arrival (AOA), angle of departure (AOD) and Doppler shifts estimation. Our predictor utilizes the transmit spatial, frequency, receive spatial and temporal correlations of the channel to extract the parameters of the dominant clusters and apply these to predict future states of the channel. Estimation of the channel parameters in stages in the proposed algorithm offers a number of potential benefits viz:

- Reduction in the number of parameters to be estimated,
- Increased number of rays that can be resolved using the limited number of available samples, and
- Improved overall prediction performance.

The remainder of the paper is organized as follows. In Section II, we present a description of the double directional cluster based channel model. The proposed algorithm is presented in section III. Section IV present results of numerical simulations and performance comparison. Finally, we draw conclusions in section V.

II. Channel Model

We consider a ray-based wideband spatial MIMO channel model for the development of the prediction scheme in this paper. This model is an extension of the continuous time impulse response of doubly selective single input single output (SISO) fading channels defined as

$$h(t;\tau) = \sum_{c=1}^{C(t)} \alpha_c(t)\delta(\tau - \tau_c(t)) \qquad (1)$$

where t and τ denote time and delay variables respectively. $C(t)$ is the time-varying number of clusters[1], and $\alpha_c(t)$ and $\tau_c(t)$ are the scattering co-efficient and delay of the cth cluster,

[1]The term cluster will be used interchangeably with path to refer to a group of rays with closely spaced delays.

respectively. We assume that the number of clusters is fixed and subsequently remove the time dependence of C. We also assume that the scatterers are in the far field of both the transmit and receive antennas so that the propagating waves can be modelled as plane waves. The scattering coefficient of the cth cluster can therefore be defined as

$$\alpha_c(t) = \sum_{r=1}^{R_c} \beta_{r,c} \exp(j\nu_{r,c}t) \tag{2}$$

where R_c is the number of rays within the cth cluster, $\beta_{r,c}$ and $\nu_{r,c} = 2\pi v_m \cos(\theta_v)/\lambda$ are the complex amplitude and Doppler frequency of the rth ray in the cth cluster, respectively. v_m is the mobile velocity, λ is the carrier wavelength and θ_v is the angle between the rth ray in the cth cluster and the direction of motion of the receiver. (2) can be extended to the modelling of a MIMO channel with M transmit and N receive antennas via the introduction of the transmit and receive array structures as

$$\mathbf{H}_c(t) = \sum_{r=1}^{R_c} \beta_{r,c} \mathbf{a}_r(\theta_{r,c}) \mathbf{a}_t^T(\phi_{r,c}) \exp(j\nu_{r,c}t) \tag{3}$$

where $[\cdot]^T$ denotes the non-conjugate transpose of the associated matrix. $\mathbf{a}_r(\theta_{r,c})$ and $\mathbf{a}_t(\phi_{r,c})$ are the receive and transmit array response vectors, respectively. $\theta_{r,c}$ and $\phi_{r,c}$ are the angles of arrival and angles of departure, respectively. Note that (3) holds for any array geometry at either end of the link. We will consider MIMO-OFDM systems with uniform linear arrays (ULA) at both ends of the link. The receive steering vector for the N element array is thus

$$\mathbf{a}_r(\theta_{r,c}) = [1, \exp(j\Omega_{r,c}), \cdots, \exp(j(N-1)\Omega_{r,c}]^T \tag{4}$$

where $\Omega_{r,c} = kd_r \sin(\theta_{r,c})$. $k = 2\pi/\lambda$ is the wave number. The transmit array steering vector having M elements is defined analogously. For simplicity, we will henceforth remove the dependence of the steering vectors on the parameters. Summing (3) over the clusters and taking the Fourier transform in the delay domain, we obtain the MIMO channel frequency response as

$$\begin{aligned}\mathbf{H}(t,f) &= \sum_{c=1}^{C} \mathbf{H}_c(t) \exp(-j2\pi f \tau_c) \\ &= \sum_{c=1}^{C}\sum_{r=1}^{R_c} \beta_{r,c}\mathbf{a}_r\mathbf{a}_t^T \exp(j\nu_{r,c}t - j2\pi f\tau_c) \end{aligned} \tag{5}$$

where f is the frequency variable. Assuming that the MIMO-OFDM system has a symbol duration of Δt and subcarrier spacing Δf, the sampled frequency response is given as

$$\mathbf{H}(q,p) = \sum_{c=1}^{C}\sum_{r=1}^{R_c} \beta_{r,c}\mathbf{a}_r\mathbf{a}_t^T \exp(jq\gamma_{r,c} - jp\eta_c) \tag{6}$$

where $\gamma_{r,c} = \nu_{r,c}\Delta t$ and $\eta_c = 2\pi\Delta f \tau_c$ are the normalized radian Doppler frequency and delay, respectively.

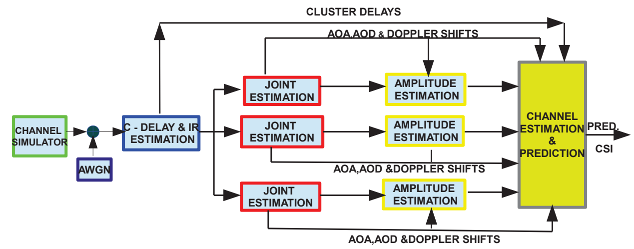

Fig. 1: Block diagram of the proposed MIMO-OFDM channel prediction scheme.

III. Proposed MIMO-OFDM Prediction Scheme

In the previous section, we presented the double directional cluster based model for wideband MIMO systems upon which the prediction scheme derived here is based. We consider a pilot based MIMO-OFDM with N_f and N_t equally spaced pilot symbols in frequency and time, respectively. We assume that the pilot channels have been estimated using suitable channel estimation techniques such as least square or minimum mean square error schemes. Due to imperfections in the channel estimates, we model the estimated frequency response as

$$\hat{\mathbf{H}}(q,p) = \mathbf{H}(q,p) + \mathbf{W}(q,p);\ q = 1,\cdots,N_t; p = 1,\cdots,N_f \tag{7}$$

where $\mathbf{W}(q,p)$ denotes the $N \times M$ channel estimation noise assumed to be complex Gaussian with zero mean and variance σ^2. Given the model in (6) and the N_tN_f channel estimates, as shown in Fig. 1, the proposed algorithm estimates the cluster delays, jointly estimates the spatial and temporal parameters of each cluster and applies the estimated parameters to predict future states of the channel.

A. Cluster Parameter Estimation

The cluster parameter estimation stage involves estimating the number of clusters and cluster delays using the channel frequency correlations followed by estimation of the cluster impulse responses. We form a Hankel matrix using the N_f frequency domain pilot channel frequency responses for each of the N_t time symbols as

$$\hat{\mathbf{D}}(q) = \begin{bmatrix} \hat{\mathbf{h}}^T(q,1) & \hat{\mathbf{h}}^T(q,2) & \cdots & \hat{\mathbf{h}}^T(q,S_f) \\ \hat{\mathbf{h}}^T(q,2) & \hat{\mathbf{h}}^T(q,3) & \cdots & \hat{\mathbf{h}}^T(q,S_f+1) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\mathbf{h}}^T(q,T_f) & \hat{\mathbf{h}}^T(q,T_f+1) & \cdots & \hat{\mathbf{h}}^T(q,N_f) \end{bmatrix} \tag{8}$$

where $\hat{\mathbf{h}}(q,p) = \text{vec}[\hat{\mathbf{H}}(q,p)]$ is the vectorised form of the channel response obtained by stacking its columns. S_f and $T_f = N_f - S_f + 1$ are the Hankel matrix size parameters which determine the size of the covariance matrix and the number of correlation averages. T_f is chosen such than $C_{\max} < T_f <$

${N_t}^2$. A rule of thumb for choosing the value of Hankel matrix size parameter is given by [13]

$$T_f = \left\lceil \frac{3}{5} N_f \right\rceil \tag{9}$$

Using the forward-backward averaging method, the frequency correlation matrix averaged over the N_t time domain pilots is obtained as

$$\hat{\mathbf{R}}_f = \frac{1}{2NMN_tS_f}\left(\hat{\mathbf{D}}\hat{\mathbf{D}}^H + \mathbf{J}\hat{\mathbf{D}}^H\hat{\mathbf{D}}\mathbf{J}\right) \tag{10}$$

where $[\cdot]^H$ denotes the Hermitian transpose, $\mathbf{J}$ is the $T_f \times T_f$ exchange matrix having ones on the anti-diagonal and zeros elsewhere.

1) Estimation of the Number of Clusters: We propose using a modified version of the minimum description length (MDL) [14] referred to as minimum mean square error (MMSE)-MDL by the authors for estimating the number of clusters. The estimate of C is defined as

$$\hat{C} = \arg \min_{1 \le u \le N_f - 1} N_f \log(\lambda_u) + \frac{1}{2}(u^2 + u)\log N_f \tag{11}$$

where $\lambda_u; u = 1, \cdots, N_f$ are the eigenvalues of the frequency correlation matrix $\hat{\mathbf{R}}_f$.

2) Cluster Delay Estimation: Similar to the SISO estimation and prediction algorithms in [6, 15], we propose an ESPRIT [16] based approach for the cluster delay estimation stage of the prediction scheme. Letting $\mathbf{V}_s$ be the signal subspace matrix containing the eigenvectors corresponding to the $\hat{C}$ largest eigenvalues of $\hat{\mathbf{R}}_f$, we form two subarray matrices with maximum overlap as

$$\begin{aligned} \mathbf{V}_{s1} &= [\mathbf{I}_{N_f-1} \quad \mathbf{0}] \\ \mathbf{V}_{s2} &= [\mathbf{0} \quad \mathbf{I}_{N_f-1}] \end{aligned} \tag{12}$$

where $\mathbf{I}_{N_f-1} \in \mathbb{R}^{(N_f-1)\times(N_f-1)}$ is the identity matrix and $\mathbf{0}$ is a $(N_f-1)\times 1$ vector of zeros. We form the 1D invariance equation as

$$\mathbf{V}_{s1}\mathbf{\Phi} = \mathbf{V}_{s1} \tag{13}$$

where $\mathbf{\Phi} \in \mathbb{C}^{N_f \times N_f}$ is a subspace rotation matrix whose eigenvalues give the normalized delay estimates. (13) can then be solved in the least square sense to obtain

$$\mathbf{\Phi} = (\mathbf{V}_{s1}^H\mathbf{V}_{s1})^{-1}\mathbf{V}_{s1}^H\mathbf{V}_{s2} \tag{14}$$

If $\{\mu_c\}_{c=1}^{\hat{C}}$ are the $\hat{C}$ eigenvalues of $\mathbf{\Phi}$, the delay of the cth cluster is estimated as

$$\hat{\tau}_c = \frac{\arg[\mu_c]}{2\pi\Delta f} \tag{15}$$

where $\arg[\cdot]$ denotes the phase of the associated complex number.

[2]We assume that the maximum number of clusters $C_{\max}$ is known *a-priori* which is reasonable since $C_{\max}$ is determined by the propagation environment.

3) Scattering Co-efficient Estimation: Once the cluster delays have been estimated, an estimate of the $\hat{C} \times N_t$ matrix $\mathcal{H}_{nm}$ containing the scattering coefficient for the channel between the nth receive and mth transmit antenna is obtained in the least square sense as

$$\hat{\mathcal{H}}_{nm} = (\mathbf{F}^H\mathbf{F} + \eta\mathbf{I})^{-1}\mathbf{F}\hat{\mathbf{H}}_{nm} \tag{16}$$

where η is the regularizing parameter introduced to minimize the effects of cluster delay estimation error on the solution of (16). η is chosen empirically as $\eta = 10^{-6}$ in this paper. $\mathbf{F}$ is the $N_f \times \hat{C}$ Fourier transform matrix with $[\mathbf{F}]_{a,b} = \exp(-j2\pi a\Delta f\tau_b)$ and $\hat{\mathbf{H}}_{nm}$ is a $N_f \times N_t$ matrix containing the estimated frequency domain pilot channel between the nth receive and mth transmit antenna elements over the N_t pilot symbol periods. Estimates of the MIMO channel response for the cth cluster at the qth time instant is obtained from the solutions of (16) as

$$\hat{\mathbf{H}}_c(q) = \begin{bmatrix} \hat{\mathcal{H}}_{11}(c,q) & \hat{\mathcal{H}}_{12}(c,q) & \cdots & \hat{\mathcal{H}}_{1M}(c,q) \\ \hat{\mathcal{H}}_{21}(c,q) & \hat{\mathcal{H}}_{22}(c,q) & \cdots & \hat{\mathcal{H}}_{2M}(c,q) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\mathcal{H}}_{N1}(c,q) & \hat{\mathcal{H}}_{N2}(c,q) & \cdots & \hat{\mathcal{H}}_{NM}(c,q) \end{bmatrix} \tag{17}$$

B. Joint Angle and Doppler Estimation

Given the estimates in (17) and the model in (3), the AOA, AOD and Doppler shifts can be jointly extracted for the rays within each of the $\hat{C}$ clusters. We propose a 3D ESPRIT based approach for the joint estimation. Using the N_t estimates in (17), we estimate the spatio-temporal correlation matrix for the cth cluster as

$$\hat{\mathbf{R}}_t^c = \frac{1}{2S_t}\left(\hat{\mathbf{D}}_c\hat{\mathbf{D}}_c^H + \mathbf{J}\hat{\mathbf{D}}_c^H\hat{\mathbf{D}}_c\mathbf{J}\right) \tag{18}$$

where $\hat{\mathbf{D}}_c$ is a $NMT_t \times S_t$ Hankel matrix defined as

$$\hat{\mathbf{D}}_c = \begin{bmatrix} \hat{\mathbf{h}}_c(1) & \hat{\mathbf{h}}_c(2) & \cdots & \hat{\mathbf{h}}_c(S_t) \\ \hat{\mathbf{h}}_c(2) & \hat{\mathbf{h}}_c(3) & \cdots & \hat{\mathbf{h}}_c(S_t+1) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\mathbf{h}}_c(T_t) & \hat{\mathbf{h}}_c(T_t+1) & \cdots & \hat{\mathbf{h}}_c(N_t) \end{bmatrix} \tag{19}$$

and $\hat{\mathbf{h}}_c(q)$ is the $NM \times 1$ vector obtained by stacking the columns of $\hat{\mathbf{H}}_c(q)$, $T_t = N_t - S_t + 1$. T_t can also be chosen using the rule in (9). However, since the size of $\hat{\mathbf{D}}_t$, and hence $\hat{\mathbf{R}}_t^c$, depends on the number of transmit and receive antennas, the complexity of the estimation algorithms will grow with the number of antennas. In order to overcome this limitation, we choose T_t using

$$T_t = \left\lceil \frac{3N_t}{5NM} \right\rceil \tag{20}$$

1) Estimation of the Number of Rays: The number of rays R_c is estimated as $\hat{R}_c$ using the MMSE-MDL given in (11) with the eigenvalues of $\hat{\mathbf{R}}_f$ replaced with the eigenvalues of $\hat{\mathbf{R}}_t^c$ and N_f with N_t.

2) ESPRIT Based Angle and Doppler Estimation: Let $\mathbf{E}_s$ be the signal subspace matrix containing the eigenvectors corresponding to the $\hat{R}_c$ largest eigenvalues of $\hat{R}_t^c$. Similar to the 1D ESPRIT approach [16], we form three invariance equations corresponding to the transmit and receive and Doppler dimensions as

$$\begin{aligned}\mathbf{J}_{R1}\mathbf{E}_s &= \mathbf{J}_{R2}\mathbf{E}_s\mathbf{\Theta}_R \\ \mathbf{J}_{T1}\mathbf{E}_s &= \mathbf{J}_{T2}\mathbf{E}_s\mathbf{\Theta}_T \\ \mathbf{J}_{D1}\mathbf{E}_s &= \mathbf{J}_{D2}\mathbf{E}_s\mathbf{\Theta}_D\end{aligned} \tag{21}$$

where $\mathbf{\Theta}_R$, $\mathbf{\Theta}_T$ and $\mathbf{\Theta}_D$ are subspace rotation matrices corresponding to the receive, transmit and Doppler dimensions, respectively. The selection matrices for the receive spatial dimension are defined as

$$\begin{aligned}\mathbf{J}_{R1} &= \mathbf{I}_M \otimes \mathbf{I}_{T_t} \otimes \left[\mathbf{I}_{(N-1)} \quad \mathbf{0_{(N-1)}}\right] \\ \mathbf{J}_{R2} &= \mathbf{I}_M \otimes \mathbf{I}_{T_t} \otimes \left[\mathbf{0}_{(N-1)} \quad \mathbf{I_{(N-1)}}\right]\end{aligned} \tag{22}$$

The selection matrices for the other dimensions are defined analogously. The subspace rotation matrices in (21) are obtained via a least square solution of the equations as

$$\begin{aligned}\mathbf{\Theta}_R &= ((\mathbf{J}_{R2}\mathbf{E}_s)^H(\mathbf{J}_{R2}\mathbf{E}_s))^{-1}(\mathbf{J}_{R2}\mathbf{E}_s)^H(\mathbf{J}_{R1}\mathbf{E}_s) \\ \mathbf{\Theta}_T &= ((\mathbf{J}_{T2}\mathbf{E}_s)^H(\mathbf{J}_{T2}\mathbf{E}_s))^{-1}(\mathbf{J}_{T2}\mathbf{E}_s)^H(\mathbf{J}_{T1}\mathbf{E}_s) \\ \mathbf{\Theta}_D &= ((\mathbf{J}_{D2}\mathbf{E}_s)^H(\mathbf{J}_{D2}\mathbf{E}_s))^{-1}(\mathbf{J}_{D2}\mathbf{E}_s)^H(\mathbf{J}_{D1}\mathbf{E}_s)\end{aligned} \tag{23}$$

Similar to [17], it can be shown that the eigendecompositions of $\mathbf{\Theta}_R$, $\mathbf{\Theta}_T$ and $\mathbf{\Theta}_D$ give estimates of $\Omega_{r,c}$, $\Psi_{r,c}$ and $\gamma_{r,c}$ respectively. However, this requires an additional stage for pairing the parameter estimates which is typically done using simultaneous Schur decomposition [18]. This scheme, however, increases the complexity of the entire algorithm significantly. In order to achieve automatic pairing of the estimates and minimize the additional complexity resulting from parameter pairing, we utilize the mean eigenvalue decomposition (MEVD) [19]. Denoting

$$\begin{aligned}\mathbf{\Theta} &= \mathbf{\Theta}_R + \mathbf{\Theta}_T + \mathbf{\Theta}_D \\ &= \mathbf{T}\mathbf{\Lambda}\mathbf{T}^{-1}\end{aligned} \tag{24}$$

where $\mathbf{T}$ denotes the common eigenvector matrix and $\mathbf{\Lambda}$ is the diagonal matrix containing the eigenvalues of $\mathbf{\Theta}$. The $\hat{R}_c$ eigenvalues for each dimension are then obtained using

$$\begin{aligned}\mathbf{\Lambda}_R &= \mathrm{diag}[\mathbf{T}^{-1}\mathbf{\Theta}_R\mathbf{T}] \\ \mathbf{\Lambda}_T &= \mathrm{diag}[\mathbf{T}^{-1}\mathbf{\Theta}_T\mathbf{T}] \\ \mathbf{\Lambda}_D &= \mathrm{diag}[\mathbf{T}^{-1}\mathbf{\Theta}_D\mathbf{T}]\end{aligned} \tag{25}$$

where $\mathrm{diag}[\cdot]$ contains the diagonal entries of the associated matrix. The parameter estimates for the rth ray in the cth cluster are given by

$$\begin{aligned}\hat{\Omega}_{r,c} &= -\arg[\mathbf{\Lambda}_R(r)] \\ \hat{\Psi}_{r,c} &= -\arg[\mathbf{\Lambda}_T(r)] \\ \hat{\gamma}_{r,c} &= \arg[\mathbf{\Lambda}_D(r)]\end{aligned} \tag{26}$$

3) Complex Amplitude Estimation: Once the parameters of the rays within each of the clusters have been estimated, estimation of the complex amplitudes $\beta_{r,c}$ of (3) can be achieved in a least square sense. Let $\hat{\mathbf{h}}_{11}^c$ be the $1 \times N_t$ vector obtained from the cth row of $\mathcal{H}_{11}$, the complex amplitudes of the rays in the cth cluster are obtained from

$$\hat{\boldsymbol{\beta}}_c = (\mathbf{G}_c^H\mathbf{G}_c + \eta\mathbf{I})^{-1}\mathbf{G}_c\hat{\mathbf{h}}_{11}^c \tag{27}$$

where $\hat{\boldsymbol{\beta}}_c = [\hat{\beta}_{1,c}, \cdots, \hat{\beta}_{\hat{R}_c,c}]^T$ and the $N_t \times \hat{R}_c$ Vandermonde structured matrix $\hat{\mathbf{G}}_c$ is defined as

$$\hat{\mathbf{G}}_c = \begin{bmatrix} 1 & \cdots & 1 \\ \exp(j\gamma_{1,c}) & \cdots & \exp(j\gamma_{\hat{R}_c,c}) \\ \vdots & \ddots & \vdots \\ \exp(j(N_t-1)\gamma_{1,c}) & \cdots & \exp(j(N_t-1)\gamma_{\hat{R}_c,c}) \end{bmatrix} \tag{28}$$

It should be noted that although we estimated the complex amplitudes using only one entry of the MIMO channel in (27) for complexity reasons, a possibly improved estimate can be obtained by formulating expressions analogous to (27) for all other entries of the CSI matrix and finding a common solution for all the equation sets. The complexity of this approach will however increase with increasing number of antennas.

C. Channel Prediction

Having estimated the parameters of the doubly selective channel, prediction of the channel is achieved by substituting the parameters into the model for the desired frequency and temporal instants. The predicted CSI is thus

$$\tilde{\mathbf{H}}(q+\Delta, p) = \sum_{c=1}^{\hat{C}}\sum_{r=1}^{\hat{R}_c}\hat{\beta}_{r,c}\hat{\mathbf{a}}_r\hat{\mathbf{a}}_t^T\exp(j((q+\Delta)\hat{\gamma}_{r,c} - p\hat{\eta}_c)) \tag{29}$$

where $q+\Delta$ denotes the time index of the predicted channel.

IV. NUMERICAL SIMULATION

In this section, we analyse the performance of the proposed prediction scheme compared to previous methods. We consider a pilot based MIMO-OFDM system, where the channel is generated using the WINNER II SCM model [11] with the parameters shown in Table I. Other model parameters retain their default values. Since previous methods for wideband MIMO prediction in open literature do not account for the spatial structure of the channel, the proposed scheme is not directly comparable with any of these methods. A possible method to which the new scheme can be compared is the multivariate linear prediction approach. This method has, however, been shown in [20] using both synthesized and measured channel data to be unreliable for MIMO channels with dense scattering. We therefore, compare our algorithm with an application of univariate linear prediction schemes that performs prediction in the time-domain on the cluster scattering coefficients in (16). The order of the linear prediction filter is set to $\ell = 20$ and we apply the Burg algorithm [21] for estimating the prediction coefficients.

TABLE I: Simulation Parameters

Parameter	Value
Number of antenna pairs (BS,MS)	N=2,4; M=2,4
BS antenna spacing	$1/2\lambda$
MS antenna spacing	$1/2\lambda$
Channel Model	3GPP/WINNER II
Scenario	Urban Macro (UMA)
Carrier frequency	2.6 GHz
Mobile Velocity	50 Kmph
Bandwidth	20 MHz
Number of Subcarriers	1024
Number of Pilot Subcarriers	48
Sampling Interval	2 ms
Training length	500

A. *Performance Comparison*

We evaluate the performance of the algorithms in terms of the normalized mean square error (NMSE) averaged over 1000 channel realizations. In Figure 2, we present the NMSE versus prediction horizon (in wavelengths) for the proposed algorithm compared to the autoregressive (AR) model based prediction [3]. Clearly, the proposed algorithm outperforms the linear prediction method for all antenna sizes simulated. A plausible explanation for the performance gain is the super resolution of the parameter estimation stage of the proposed algorithm and the utilization of both spatial and temporal statistics of the channel. Similar observations have been made in [22] while studying bounds on the prediction of narrowband MIMO channels.

A plot of the NMSE as a function of SNR is presented in Fig. 3. As expected, the performance of both prediction algorithms improves with increasing SNR. However, the performance gain offered by the proposed algorithm also increases with SNR. For instance, while the difference between the NMSE of the proposed algorithm and AR prediction method at $\mathrm{SNR} = 0\,\mathrm{dB}$ is about $8\,\mathrm{dB}$, the gain in NMSE increases to $25\,\mathrm{dB}$ at $\mathrm{SNR} = 30\,\mathrm{dB}$. This is due to the improved parameter estimation accuracy at high SNR.

Finally, we present a plot of the NMSE versus antenna sizes in Fig. 4. We observe that increasing the number of transmit and/or receive antenna elements improves the performance of the proposed algorithm, in contrast to the AR prediction performance which is approximately constant for all antenna sizes. This is expected since the AR prediction method treats the entries of the MIMO channel as NM independent SISO channels. Since ESPRIT based schemes provide computationally efficient approach for model parameter extraction, we believe that the complexity of our algorithm is comparable to previous methods. However, detailed evaluation of the computational complexity is left for future work due to space constraints.

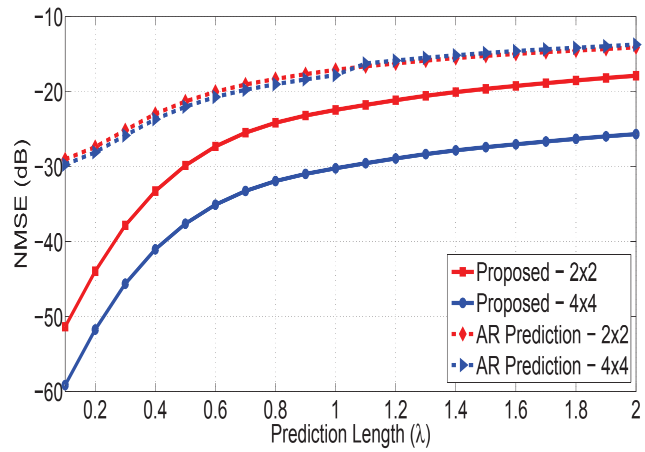

Fig. 2: Normalized mean square prediction error versus prediction length at $\mathrm{SNR} = 10\,\mathrm{dB}$ using the proposed prediction algorithm and an application of AR based prediction on the time domain cluster scattering co-efficients for each antenna pair.

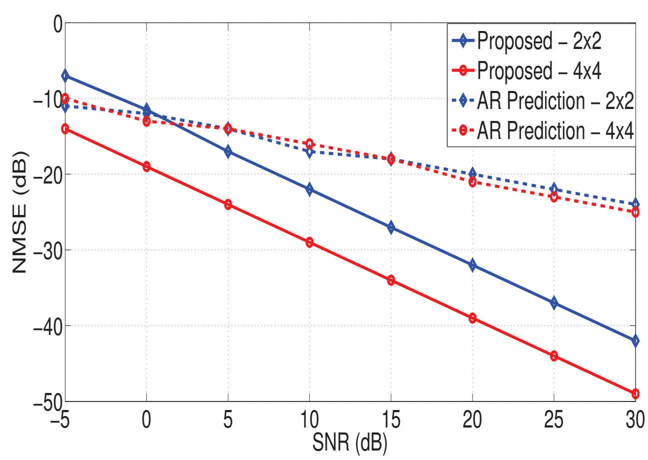

Fig. 3: Normalized mean square prediction error versus SNR for a prediction length of $1\,\lambda$ using the proposed prediction algorithm and an application of AR based prediction on the time domain cluster scattering co-efficients for each antenna pair.

V. Conclusion

We proposed a new algorithm for the prediction of a realistic double directional and doubly selective MIMO-OFDM spatial channel. The proposed algorithm estimates the cluster delay and scattering coefficients via a 1D ESPRIT approach and utilizes a 3D ESPRIT based scheme to jointly estimate the angles of arrival, angles of departure and Doppler shifts. The estimated parameters are then used to extrapolate the channel using the model. Simulation results using the industry standard 3GPP/WINNER II spatial channel model show that the proposed algorithm offers improved prediction performance over previous schemes with similar computational complexity. Future work will evaluate the performance of the proposed method using real measured channel data.

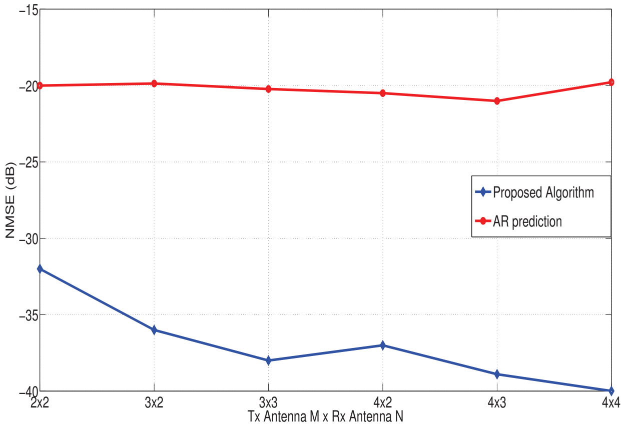

Fig. 4: Normalized mean square prediction error versus Number of antenna elements for a prediction length of $1\,\lambda$ using the proposed prediction algorithm and an application of AR based prediction on the time domain cluster scattering co-efficients for each antenna pair at $\mathrm{SNR} = 20\,\mathrm{dB}$.

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