Parametric Channel Prediction for Narrowband MIMO Systems Using Polarized Antenna Arrays

Ramoni O. Adeogun, Paul D. Teal and Pawel A. Dmochowski
School of Engineering and Computer Science, Victoria University of Wellington, Wellington, New Zealand
E-mail:{*ramoni.adeogun,paul.teal,pawel.dmochowski*}*@ecs.vuw.ac.nz*

***Abstract*—A novel prediction scheme for polarized narrowband MIMO channels is proposed in this paper. The prediction scheme is based on estimation of the parameters of a double directional polarized propagation model. The proposed algorithm transforms the channel impulse response matrix in such a manner that a multidimensional extension of the ESPRIT algorithm can be utilized to jointly estimate the angles of arrival, angles of departure, Doppler shifts and complex polarimetric weights of the dominant multipath components. Simulation results show that the proposed algorithm outperforms repeated application of one dimensional ESPRIT based approach with similar computational complexity.**

***Index Terms*—Polarized MIMO, ESPRIT, Channel Prediction, Parameter Estimation.**

I. Introduction

Next generation wireless communication systems are faced with the challenge of providing high data rate and improved Quality of Service (QoS) for an increasing number of users. This requires transmission schemes and receiver algorithms that offer significant increases in spectral efficiency. To this end, adaptive and limited feedback multiple input multiple output (MIMO) systems are being considered. Recently, MIMO systems having dual polarized antenna pairs at the transmitter and/or receiver have been adopted as the antenna configuration of choice in wireless standards such as 3GPP-LTE/LTE-Advanced. This is due primarily to the potential of decreasing antenna correlation and increasing achievable capacity by deploying more antennas within limited space constraints [1]. A common problem with adaptive transmission schemes and feedback based MIMO is that channel state information at the transmitter (CSIT) is often outdated before it can be used because of the changes in the channel and delay in the feedback link. Extrapolation of the CSI into the future has however been shown to mitigate the performance degradation resulting from using outdated CSIT for link adaptation [2] and/or precoding. In [3], the effects of channel aging on the performance of massive MIMO systems was analysed. It was shown that significant capacity is lost due to aging of time varying channels.

Channel state prediction has been well addressed in the literature for SISO systems (see e.g [4, 5]) and some publications exist on the prediction of MIMO channels. However, to the authors' knowledge, there exist no publication in the open literature on the prediction of polarized MIMO channels. In [6], an autoregressive model (AR) based predictor with a beamspace transformation scheme was proposed for narrowband MIMO channels. The authors of [7] extended the classical ESPRIT based SISO prediction scheme to MIMO channels. This approach does not utilize the additional information offered by multiple sampling of the channel. The authors of [8] proposed a prediction algorithm using Doppler-delay analysis for coordinated multi-point cellular systems. It was shown that the performance of base station cooperation is improved by predicting the channel. This approach is however, not directly applicable to MIMO systems with collocated antenna elements. In [9], a parametric prediction for narrowband MIMO systems that exploits the receive spatial and temporal correlations in realistic spatial channel models was proposed. Polarization diversity and differences in modelling between polarized and non-polarized MIMO systems make these schemes unsuitable for the prediction of polarized MIMO channels.

Motivated by the benefit of CSI prediction for adaptive and limited feedback schemes and the gains of using polarized antenna configurations, we make the following contributions in this paper.

- Based on the industry standard 3GPP/WINNER II channel model [10], we derive a parametrized model for polarized MIMO in 2D environments.
- We propose a transformation to convert the channel impulse response into three dimensional array data such that a sufficiently large data matrix satisfying some invariance structure is obtained.
- We provide an original adaptation of multidimensional ESPRIT [11] to jointly estimate the parameters of polarized MIMO channels and use the estimates for prediction.

II. Channel Models

In this section, we present a brief review of the standardized WINNER II channel model and derive a parametrization of the model on which the prediction scheme of Section III is based.

A. 2D Polarized MIMO Spatial Channel Model

Consider a feedback based narrowband MIMO system with a uniform linear array (ULA) of dual-polarized antenna pairs (see Fig. 1) at both the base station (BS) and mobile station (MS). Assuming that the BS and MS arrays have N and M antenna pairs, respectively and that the propagation environment is characterized by P far field scatterers, the channel between the nth transmit and mth receive antenna pair is given by [10]

$$h_{m,n}(t) = \sum_{p=1}^{P} \begin{bmatrix} \mathcal{X}_{T,v}^{n} \\ \mathcal{X}_{T,h}^{n} \end{bmatrix}^{*} \begin{bmatrix} \exp(j\Phi_p^{vv}) & \sqrt{\kappa_p}\exp(j\Phi_p^{vh}) \\ \sqrt{\kappa_p}\exp(j\Phi_p^{hv}) & \exp(j\Phi_p^{hh}) \end{bmatrix} \times \begin{bmatrix} \mathcal{X}_{R,v}^{m} \\ \mathcal{X}_{R,h}^{m} \end{bmatrix} \exp(j(n-1)\varphi_p + j(m-1)\Omega_p + j2\pi\nu_p t) \tag{1}$$

where $(\cdot)^*$ denotes the Hermitian transpose, P is the number of scattering sources, $\Omega_p = 2\pi\delta r\sin\theta_p$ and $\varphi_p = 2\pi\delta t\sin\phi_p$. δr and δt are the spacings between the receive and transmit antenna pairs, respectively. ϕ_p and θ_p are the angle of departure (AOD) and angle of arrival (AOA) of the pth scattering source respectively. $[\Phi_p^{\mathrm{vv}}, \Phi_p^{\mathrm{vh}}, \Phi_p^{\mathrm{hv}}, \Phi_p^{\mathrm{hh}}] \sim U(-\pi, \pi)$ are the random initial phases of the pth path for the four polarization components. $\mathcal{X}_{\mathrm{T,v}}^{n}$ and $\mathcal{X}_{\mathrm{T,h}}^{n}$ are the nth transmit antenna element field patterns for the vertical and horizontal polarizations, respectively. $\mathcal{X}_{\mathrm{R,v}}^{m}$ and $\mathcal{X}_{\mathrm{R,h}}^{m}$ are the mth receive antenna element field patterns. The cross polarization power ratio (XPR) for the pth path, $\kappa_p = 10^{X/10}$, (where $X \sim \mathcal{N}(\sigma, u)$) is assumed to be log-Normal distributed. $\nu_p = \frac{v\cos(\theta_p - \vartheta_v)}{\lambda}$ is the Doppler shift of the pth path. Finally, v, ϑ_v and λ are the mobile speed, direction of motion and carrier wavelength, respectively. If (for example) the BS and MS have ideal dipole antennas tilted at α from the vertical axis and the antenna polarization leakage effects can be neglected, the antenna field pattern for the pth path would be given by [1]

$$\mathcal{X}_{\mathrm{R}} = \begin{bmatrix} \mathcal{X}_{\mathrm{R,v}} \\ \mathcal{X}_{\mathrm{R,h}} \end{bmatrix} = \begin{bmatrix} \cos\alpha \\ \sin\alpha\cos\theta \end{bmatrix} \tag{2}$$

B. Parametrized Prediction Model

In order to characterize the spatial structure and polarization diversity of the polarized MIMO channel, a matrix representation of the model in (1) is required. Collecting the $4NM$ channels in (1) into a matrix, we obtain

$$\mathbf{H}(t) = \begin{bmatrix} h_{1,1} & h_{2,1} & \cdots & h_{2N,1} \\ \vdots & \vdots & \ddots & \vdots \\ h_{2M,1} & h_{2M,2} & \cdots & h_{2M,2N} \end{bmatrix} \tag{3}$$

Using the model in (1), the $2M \times 2N$ polarized MIMO channel impulse response (3) is given by

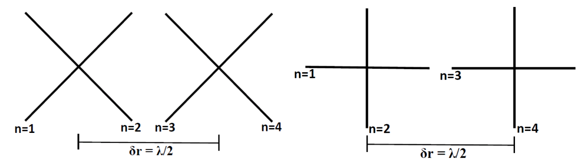
$$\mathbf{H}(t) = \sum_{p=1}^{P} \mathcal{S}_{\mathrm{T}}^{*}(\phi_p)\mathbf{G}_p\mathcal{S}_{\mathrm{R}}(\theta_p)\exp(j2\pi k\nu_p t) \tag{4}$$

where

$$\mathbf{G}_p = \begin{bmatrix} g_p^{\mathrm{vv}} & g_p^{\mathrm{vh}} \\ g_p^{\mathrm{hv}} & g_p^{\mathrm{hh}} \end{bmatrix} \in \mathbb{C}^{2\times 2} \tag{5}$$

is the polarimetric weight matrix. $\mathcal{S}_{\mathrm{R}}(\theta_p) \in \mathbb{C}^{2\times 2M}$ is the receive polarized array steering matrix defined as

$$\mathcal{S}_{\mathrm{R}}(\theta_p) = \mathbf{a}_{\mathrm{R}}(\theta_p) \otimes \begin{bmatrix} \cos\alpha_1 & \cos\alpha_2 \\ \sin\alpha_1\cos\theta_p & \sin\alpha_2\cos\theta_p \end{bmatrix} \tag{6}$$



(a) -45/45 (b) 0/90

Fig. 1: Polarized MIMO Antenna Configurations: (a) Slanted 45 configuration and (b) VV/HH configuration.

where $\otimes$ denotes the Kronecker product, α_1 and α_2 are the slant angles and $|\alpha_1 - \alpha_2| = \pi/2$. The array steering vector $\mathbf{a}_{\mathrm{R}}(\theta_p) \in \mathbb{C}^{1\times M}$ is defined for a ULA as

$$\mathbf{a}_{\mathrm{R}}(\theta_p) = [1 \quad \exp(-j\Omega_p) \quad \cdots \quad \exp(-j(M-1)\Omega_p)]^T \tag{7}$$

The transmit polarized steering matrix is analogously obtained by replacing θ_p with ϕ_p in (6) and Ω_p with φ_p in (7). Assuming that the sampling interval is Δt, the sampled channel at the k time instant is thus

$$\mathbf{H}(k) = \sum_{p=1}^{P} \mathcal{S}_{\mathrm{T}}^{*}(\phi_p)\mathbf{G}_p\mathcal{S}_{\mathrm{R}}(\theta_p)\exp(j2\pi k\nu_p\Delta t) \tag{8}$$

The parameters $\mathbf{G}_p$, θ_p, ϕ_p and ν_p are assumed constant over the region of interest. This assumption has been shown in the industry standard 3GPP/WINNER II SCM model [10, p. 55] to be valid for mobile movements up to 50λ. We also assume that K samples of the CSI matrix are available either by transmitting known pilot sequences or from measurement. In practice, the estimated or measured channel will have some imperfections due to the effects of noise and interference. The estimated CSI matrix at time instant k is therefore defined as

$$\hat{\mathbf{H}}(k) = \mathbf{H}(k) + \mathcal{W}(k) \tag{9}$$

where $\mathcal{W}(k) \in \mathbb{C}^{2M\times 2N}$ is a complex Gaussian random variable that accounts for the effect of measurement/estimation noise and multiuser interference.

III. Proposed Predictor

Given the K estimates of the channel and the model in (6), our aim is to estimate the parameters of the polarized MIMO channel and use the estimated parameters for the prediction of the CSI into the future. The different stages involved in the proposed prediction algorithm are presented in this section.

A. Data Preprocessing and Covariance Matrix Estimation

In order to jointly estimate the parameters of the channel using ESPRIT, we need to transform the CSI matrix such that the invariance structure requirement [12] is satisfied. Since the two elements of each antenna pair occupy the same location, the channels between these pairs contain the same information about the AOA and AOD although the polarization dependant of complex gains are different. Consequently, the invariance structure is not satisfied and we form four subsets (corresponding to the four polarization components) from the CSI matrix, given by

$$\hat{\mathbf{D}}_{ij}(k) = \begin{bmatrix} \hat{h}_{i,j}(k) & \hat{h}_{i,j+2}(k) & \cdots & \hat{h}_{i,m_j}(k) \\ \hat{h}_{i+2,j}(k) & \hat{h}_{i+2,j+2}(k) & \cdots & \hat{h}_{i+2,m_j}(k) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{h}_{n_i,j}(k) & \hat{h}_{n_i,j+2}(k) & \cdots & \hat{h}_{n_i,m_j}(k) \end{bmatrix} \quad (10)$$

where $\hat{h}_{i,j}(k)$ is the (i,j)th entry of $\hat{\mathbf{H}}(k)$, $n_i = (2N+i-2)$ and $m_j = (2M+j-2)$ and $i,j = 1,2$. The four submatrices specified in (10) correspond to the four possible polarization combinations in a polarized MIMO channel. This is to ensure that entries of the submatrices are phase shifted versions of each other as required for parameter extraction using ESPRIT [12]. Letting $\hat{\mathbf{d}}_{ij}(k) = \text{vec}[\hat{\mathbf{D}}_{ij}(k)]$ be the vectorized form of $\hat{\mathbf{D}}_{ij}(k)$ obtained by stacking its column, we form an $NMR \times L$ Hankel matrix for each polarization conbination denoted by

$$\hat{\mathbf{Q}}_{ij} = \begin{bmatrix} \hat{\mathbf{d}}_{ij}(1) & \hat{\mathbf{d}}_{ij}(2) & \cdots & \hat{\mathbf{d}}_{ij}(L) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\mathbf{d}}_{ij}(R) & \hat{\mathbf{d}}_{ij}(R+1) & \cdots & \hat{\mathbf{d}}_{ij}(K) \end{bmatrix} \quad i,j = 1,2 \quad (11)$$

where $L = K - R + 1$ and R is chosen such that $NMR \geq P + 1$. The data in $\hat{\mathbf{Q}}_i$ is equivalent to L observations from an $N \times M \times R$ three dimensional antenna array. It should however be noted that the data is obtained by combining the receive spatial, temporal and transmit spatial samples of the channel. The spatio-temporal covariance matrix averaged over the four polarization components is then estimated using

$$\hat{\mathbf{C}} = \frac{1}{4L} \sum_{i=1}^{2} \sum_{j=1}^{2} (\hat{\mathbf{Q}}_{ij} \hat{\mathbf{Q}}_{ij}^{*}) \quad (12)$$

B. Subspace Dimension and Joint Parameter Estimation

A commonly used approach for estimating the number of scattering sources is the Minimum Description Length (MDL) information theoretic criterion. Let $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \cdots \geq \hat{\lambda}_{NMR}$ be the eigenvalues of $\hat{\mathbf{C}}$ in descending order of magnitude, and $\hat{\mathbf{e}}_1, \hat{\mathbf{e}}_2, \cdots, \hat{\mathbf{e}}_{NMR}$ the associated eigenvectors. The estimate of the number of paths is obtained from [13]

$$\hat{P} = \arg \min_{p=1,\cdots,NMR-1} L \log(\lambda_p) + \frac{1}{2}(p^2 + p) \log L \quad (13)$$

We arrange the eigenvectors corresponding to the $\hat{P}$ largest eigenvalues of $\hat{\mathbf{C}}$ into a matrix $\mathbf{E} = [\hat{\mathbf{e}}_1, \cdots, \hat{\mathbf{e}}_{\hat{P}}]$ and form the following invariance equations

$$\mathbf{S}_{\theta 2}\mathbf{E} = \mathbf{S}_{\theta 1}\mathbf{E}\boldsymbol{\Theta} \quad \mathbf{S}_{\phi 2}\mathbf{E} = \mathbf{S}_{\phi 1}\mathbf{E}\boldsymbol{\Phi} \quad \mathbf{S}_{\nu 2}\mathbf{E} = \mathbf{S}_{\nu 1}\mathbf{E}\mathbf{N} \quad (14)$$

where $\boldsymbol{\Theta}$, $\boldsymbol{\Phi}$ and $\mathbf{N}$ are subspace rotation matrices, the eigenvalues of which provide information about the AOA, AOD and Doppler shifts, respectively, and $\mathbf{S}_{xi}; i = 1,2$ are selection matrices defined as

$$\begin{aligned} \mathbf{S}_{\theta 1} &= \mathbf{I}_M \otimes \mathbf{I}_R \otimes \begin{bmatrix} \mathbf{I}_{(N-1)} & \mathbf{0}_{(\mathbf{N-1})} \end{bmatrix} \\ \mathbf{S}_{\theta 2} &= \mathbf{I}_M \otimes \mathbf{I}_R \otimes \begin{bmatrix} \mathbf{0}_{(N-1)} & \mathbf{I}_{(\mathbf{N-1})} \end{bmatrix} \end{aligned} \quad (15)$$

where $\mathbf{I}_D$ is an $D \times D$ identity matrix and $\mathbf{0}_D \in \mathbb{R}^D$ is an D-dimensional vector of zeros. $\mathbf{S}_{\phi i}$ and $\mathbf{S}_{\nu i}$ are defined analogously. The equations in (14) are then solved in a least square sense to obtain

$$\begin{aligned} \boldsymbol{\Theta} &= ((\mathbf{S}_{\theta 2}\mathbf{E})^*(\mathbf{S}_{\theta 2}\mathbf{E}))^{-1}(\mathbf{S}_{\theta 2}\mathbf{E})^*(\mathbf{S}_{\theta 1}\mathbf{E}) \\ \boldsymbol{\Phi} &= ((\mathbf{S}_{\phi 2}\mathbf{E})^*(\mathbf{S}_{\phi 2}\mathbf{E}))^{-1}(\mathbf{S}_{\phi 2}\mathbf{E})^*(\mathbf{S}_{\phi 1}\mathbf{E}) \\ \mathbf{N} &= ((\mathbf{S}_{\nu 2}\mathbf{E})^*(\mathbf{S}_{\nu 2}\mathbf{E}))^{-1}(\mathbf{S}_{\nu 2}\mathbf{E})^*(\mathbf{S}_{\nu 1}\mathbf{E}) \end{aligned} \quad (16)$$

Similar to [14], it can be shown that the $\hat{P}$ eigenvalues of $\boldsymbol{\Theta}$, $\boldsymbol{\Phi}$ and $\mathbf{N}$ can be used to estimate the AOA, AOD and Doppler shifts, respectively. However, an additional pairing scheme is required to correctly pair the parameter estimates. In order to achieve automatic pairing of the estimates, we instead define

$$\mathcal{Y} = \boldsymbol{\Theta} + \boldsymbol{\Phi} + \mathbf{N} = \mathbf{T}\boldsymbol{\Lambda}\mathbf{T}^{-1} \quad (17)$$

where $\mathbf{T}$ is the common eigenvector matrix and $\boldsymbol{\Lambda}$ is a diagonal matrix containing the eigenvalues of $\mathcal{Y}$. The $\hat{P}$ eigenvalues for each dimension are then computed using

$$\begin{aligned} \boldsymbol{\Lambda}_\theta &= \text{diag}[\mathbf{T}^{-1}\boldsymbol{\Theta}\mathbf{T}] \\ \boldsymbol{\Lambda}_\phi &= \text{diag}[\mathbf{T}^{-1}\boldsymbol{\Phi}\mathbf{T}] \\ \boldsymbol{\Lambda}_\nu &= \text{diag}[\mathbf{T}^{-1}\mathbf{N}\mathbf{T}] \end{aligned} \quad (18)$$

where $\text{diag}[A]$ contains the diagonal elements of A. The parameter estimates for the pth path are given by

$$\begin{aligned} \hat{\theta}_p &= \text{asin}\left(\frac{-\arg[\boldsymbol{\Lambda}_\theta(p)]}{2\pi\delta r}\right) \\ \hat{\phi}_p &= \text{asin}\left(\frac{\arg[\boldsymbol{\Lambda}_\phi(p)]}{2\pi\delta t}\right) \\ \hat{\nu}_p &= \frac{\arg[\boldsymbol{\Lambda}_\nu(p)]}{2\pi\Delta t} \end{aligned} \quad (19)$$

where $\arg[\cdot]$ denotes the phase angle of the associated complex number in the range $[0, 2\pi)$.

C. Polarimetric Weights Estimation and CSI Prediction

We assume that for a given multipath component the complex polarimetric weights for all antenna pairs are equal. This assumption is reasonable considering the separation of polarization effects from path attenuation in (4) and the small spacing between antenna elements. The complex weight matrices can therefore be estimated from the first 2×2 submatrix of the channel matrix. Let the submatrix be denoted as

$$\hat{\mathbf{H}}_{\text{SUB}}(k) = \begin{bmatrix} \hat{h}_{1,1}(k) & \hat{h}_{1,2}(k) \\ \hat{h}_{2,1}(k) & \hat{h}_{2,2}(k) \end{bmatrix} \quad (20)$$

It can be shown from (4) that entries of $\hat{\mathbf{H}}_{\text{SUB}}$ are defined as

$$\hat{h}_{i,j}(k) = \sum_{p=1}^{P} \mathbf{u}_p^{i,j} \mathbf{g}_p \exp(j2\pi(k-1)\nu_p \Delta t) + w_{i,j}(k) \quad (21)$$

where $\mathbf{g}_p = [g_p^{\text{vv}}, g_p^{\text{hv}}, g_p^{\text{vh}}, g_p^{\text{hh}}]^T$, $w_{i,j}(k)$ is the noise component and $\mathbf{u}_p^{i,j} = [\cos\alpha_i \cos\alpha_j, \cos\alpha_i \sin\alpha_j \cos\phi_p, \cos\alpha_i \sin\alpha_j \cos\theta_p,$

TABLE I: Simulation Parameters

Parameter	Value
Number of antenna pairs (BS,MS)	N=2, M=2
BS/MS antenna spacing	$1/2\lambda$
Number of Sources	10
Carrier frequency, Mobile Velocity	2.1 GHz, 50 Kmph
AOD	$U[-\pi/3, \pi/3]$
AOA	$U[-\pi/2, \pi/2)$
Sampling Interval, Training length	2 ms, 50
Dual Polarized Antenna Orientation	+45/-45, 0/90

TABLE II: Computational Complexity Comparison

Step	Proposed Algorithm	1-D ESPRIT
Covariance Matrix Estimation	$\mathcal{O}(4L\xi_3^2)$	$\mathcal{O}(4L\xi_1^2)$
Estimation of Number of Paths	$\mathcal{O}(\xi_3^3)$	$\mathcal{O}(\xi_1^3)$
Parameter Estimation	$\mathcal{O}(10\hat{P}^3 + 6\hat{P}^2\xi_3 + 6\hat{P}\xi_3^2)$	$\mathcal{O}(2\hat{P}^3 + 2\hat{P}^2\xi_1 + 3\hat{P}\xi_1^2)$
Complex Weight Estimation	$\mathcal{O}(64K\hat{P}^2)$	$\mathcal{O}(16NMK\hat{P}^2)$
Channel Prediction	$\mathcal{O}(2NM\hat{P} + \hat{P}\Delta)$	$\mathcal{O}(4NM\hat{P}\Delta)$

$\sin\alpha_i \sin\alpha_i \cos\theta_p \cos\phi_p]; i,j = 1,2$. Collecting the K known samples into a vector, we obtain

$$\hat{\mathbf{h}}_{i,j} = \sum_{p=1}^{P} (\mathbf{f}_p \otimes \mathbf{u}_p^{i,j})\mathbf{g}_p + \mathbf{w}_{i,j} \tag{22}$$

where $\hat{\mathbf{h}}_{i,j} = [\hat{h}_{i,j}(1), \cdots, \hat{h}_{i,j}(K)]^T$, $\mathbf{f}_p = [1, \cdots, \exp(j2\pi(K-1)\nu_p\Delta t)]^T \in \mathbb{C}^{K\times 1}$ and $\mathbf{w}_{i,j}$ is the noise vector. A matrix representation for (22) is thus

$$\hat{\mathbf{h}}_{i,j} = \mathbf{F}_{i,j}\mathbf{g} + \mathbf{w}_{i,j}; \quad i,j = 1,2 \tag{23}$$

where $\mathbf{F}_{i,j} = [\mathbf{f}_1 \otimes \mathbf{u}_1^{i,j}, \cdots, \mathbf{f}_P \otimes \mathbf{u}_P^{i,j}] \in \mathbb{C}^{K\times 4\hat{P}}$ and $\mathbf{g} = [\mathbf{g}_1^T; \cdots; \mathbf{g}_{\hat{P}}^T] \in \mathbb{C}^{4\hat{P}\times 1}$ is a vector containing the polarimetric weights for all scattering sources. Estimates of the polarimetric weight matrix cannot be obtained directly from (23), because the matrices $\mathbf{F}_{i,j}$ are rank deficient (with rank equal to $\hat{P}$ instead of $4\hat{P}$) and as such the least square solution may not converge to the optimal values. In order to overcome this, we combine the four equations in (23)

$$\mathbf{h} = \mathbf{F}\mathbf{g} + \mathbf{w} \tag{24}$$

where $\mathbf{h} = [\mathbf{h}_{1,1}\ \mathbf{h}_{1,2}\ \mathbf{h}_{2,1}\ \mathbf{h}_{2,2}]^T \in \mathbb{C}^{4K\times 1}$ and $\mathbf{F} = [\mathbf{F}_{1,1}\ \mathbf{F}_{1,2}\ \mathbf{F}_{2,1}\ \mathbf{F}_{2,2}]^T \in \mathbb{C}^{4K\times 4\hat{P}}$ and solve (24) using regularized least squares to obtain estimates of the weights

$$\hat{\mathbf{g}} = (\mathbf{F}^*\mathbf{F} + \eta\mathbf{I})^{-1}\mathbf{F}^*\mathbf{h} \tag{25}$$

where η is a regularizing parameter that improves the robustness of the predictor by reducing sensitivity to errors in the estimation of $\mathbf{F}$. η was chosen emprically at about 10^{-5} in this paper.

Once the parameters of the channel are estimated, the extrapolation of the polarized MIMO CSI is achieved by substituting the estimated multipath parameters into (4) for the desired prediction horizon.

IV. Performance Evaluation

The performance of the proposed algorithm is evaluated in this section. The simulation parameters are presented in Table I (except where stated otherwise). The channel parameters are assumed quasi-stationary for each realization but vary from drop to drop. As stated in Section I, there have been no previous works studying prediction of polarized channels. To make comparison possible, we therefore compare the proposed algorithm with an application of 1D ESPRIT [7]. In the 1D ESPRIT based scheme, only the Doppler frequencies of the dominant sources are estimated and each entry of the MIMO matrix is treated independently for estimation of the complex weight. In Fig. 2, we present the normalized mean square (NMSE) prediction error as a function of the prediction horizon. Since the proposed multidimensional ESPRIT based algorithm utilizes spatial, temporal and polarization information to improve the parameter estimation accuracy, it outperforms 1D ESPRIT based prediction for all prediction ranges at all SNR levels The performance difference however, increases with increasing SNR. This is possibly due to model mismatch or under-estimation of the number of sources at low SNR. In Fig. 3, we present the normalized square error (NSE) cummulative distribution function (CDF) for prediction intervals of 1λ, 5λ and 10λ at different noise levels. It shows that the algorithm can predict far into the future. The CDF plots in Fig. 4 show the effect of the number of antennas, antenna orientations and polarization on the NMSE performance of the proposed algorithm. We note that the antenna orientation does not affect the performance of the algorithm. Increasing the number of antenna pairs improves the prediction accuracy since more structure of the MIMO channel is revealed. A comparison of the plots for non-polarized and polarized prediction shows that polarization diversity can be exploited to improve the prediction by having more antennas within the same limited space. Finally, we plot the NMSE versus SNR for prediction lengths of 1λ, 2λ and 5λ in Fig. 5. We observe that the prediction error decreases with increasing SNR. However, the error difference diminishes with SNR. For instance, while increasing SNR from 0 to 5dB decreases the NMSE by about 3dB, a similar increase from 10 to 15dB only produces NMSE decrease of approximately 0.2dB.

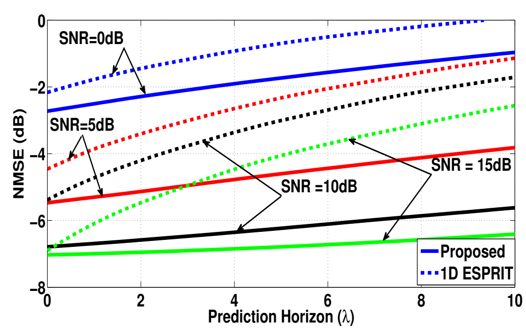


Fig. 2: NMSE vs prediction horizon for the proposed algorithm and 1D ESPRIT based scheme at different SNR values.

A. Complexity Analysis

The major computational requirement of both the proposed and 1D-ESPRIT based algorithms is accounted for by the covariance matrix estimation, source number estimation, ESPRIT based parameter estimation and complex weight estima-

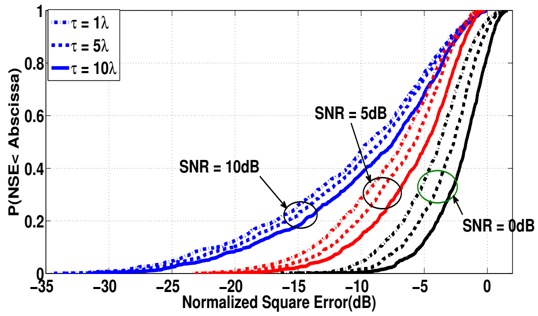


Fig. 3: NSE CDF for 1λ, 5λ and 10λ prediction at different SNR values.

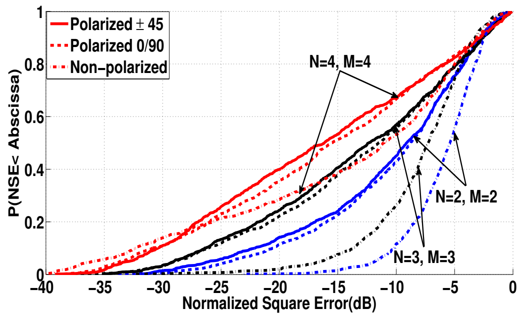


Fig. 4: The CDF of prediction NSE for a prediction length of 10 ms ($\approx 1\lambda$) at SNR = 10 dB.

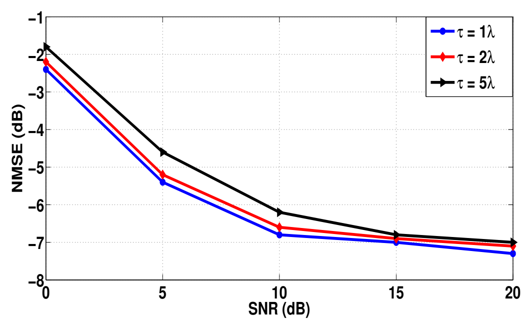


Fig. 5: NMSE versus SNR for prediction lengths of 1λ, 2λ and 5λ. The prediction initialized with 50 samples.

tion stages. The computation of the $NMR \times NMR$ spatio-temporal covariance matrix in the proposed algorithm (12) has complexity $\mathcal{O}(4L\xi_3^2)$, where $\xi_3 = NMR$. In order to allow fair comparison of the algorithms, we set $\xi_1 = \xi_3$ for temporal correlation matrix in the 1D ESPRIT based approach. Thus, the complexity for estimating the covariance matrix has same order of magnitude. Since the eigendecomposition of the covariance matrix dominates the complexity of the MMDL based estimation of number of rays (13), the computation has principal complexity $\mathcal{O}(\xi_3^3)$. The same computation is also required for the 1D ESPRIT based approach. The 3D ESPRIT and 1D ESPRIT parameter estimation stages of the two algorithms only differ in the number of matrix multiplications and inversions, and has complexity $\mathcal{O}(10\hat{P}^3 + 6\hat{P}^2\xi_3 + 6\hat{P}\xi_3^2)$ and $\mathcal{O}(2\hat{P}^3 + 2\hat{P}^2\xi_1 + 3\hat{P}\xi_1^2)$, respectively. Clearly, the complexity of the proposed algorithm is only slightly higher for this stage. The algorithms have complexity of $\mathcal{O}(64K\hat{P}^2)$ and $\mathcal{O}(16NMK\hat{P}^2)$ for the polarimetric weight estimation. Since the 1D ESPRIT based scheme compute the complex weight for each entry of the MIMO channel independently, the complexity grows with the number of antenna pairs at both ends of the link and exceeds that of the proposed algorithm for $N, M > 2$. Finally, the channel prediction stage has similar complexity for both algorithms. A summary of the computational complexity of the proposed algorithm and the 1-D ESPRIT based scheme is presented in Table II.

V. Conclusion

We have proposed an effective channel prediction algorithm for polarized narrowband MIMO channels. The proposed algorithm is based on the double directional model and an ESPRIT based multidimensional parameter estimation. The polarization diversity in the channel is utilized to improve parameter estimation accuracy. Simulation results show that the predictor can achieve useful prediction horizons even with short training lengths. Future work will evaluate the performance of the algorithm with measured data.

References

[1] M. Shafi, M. Zhang, A. L. Moustakas, P. J. Smith, A. F. Molisch, F. Tufvesson, and S. H. Simon, "Polarized MIMO Channels in 3D: Models, Measurements and Mutual Information," *IEEE J. Select. Areas Commun*, vol. 24, pp. 514–527, 2006.

[2] A. Duel-Hallen, "Fading Channel Prediction for Mobile Radio Adaptive Transmission Systems," *Proceedings of the IEEE*, vol. 95, no. 12, pp. 2299–2313, 2007.

[3] K. T. Truong and R. W. H. Jr., "Effects of channel aging in massive MIMO systems," *Journal of Communications and Networks*, vol. 15, no. 4, pp. 338–351, Aug. 2013.

[4] P. Teal and R. Vaughan, "Simulation and performance bounds for real-time prediction of the mobile multipath channel," in *IEEE Workshop on Statistical Signal Processing Proceedings*, 2001, pp. 548–551.

[5] M. Chen and M. Viberg, "Long-range channel prediction based on nonstationary parametric modeling," *Trans. Sig. Proc.*, vol. 57, no. 2, pp. 622–634, Feb 2009.

[6] K. Okino, T. Nakayama, S. Joko, Y. Kusano, and S. Kimura, "Direction based beamspace MIMO channel prediction with ray cancelling," in *PIMRC*, 2008, pp. 1–5.

[7] J. Vanderpypen and L. Schumacher, "MIMO Channel Prediction using ESPRIT based Techniques," in *International Symposium on Personal, Indoor and Mobile Radio Communications*, 2007, pp. 1–5.

[8] K. Manolakis, S. Jaeckel, V. Jungnickel, and V. Braun, "Channel prediction by doppler-delay analysis and benefits for base station cooperation," in *IEEE 77th Vehicular Technology Conference (VTC)*, Dresden, Germany, jun 2013.

[9] R. O. Adeogun, P. D. Teal, and P. A. Dmochowski, "Parametric Channel Prediction for Narrowband Mobile MIMO Systems Using Spatio-Temporal Correlation Analysis," in *IEEE Vehicular Technology Conference Fall*, sep 2013.

[10] "IST-WINNER II Deliverable 1.1.2 v.1.2, WINNER II channel models," IST-WINNER2, Tech. Rep., 2007. [Online]. Available: http://www.ist-winner.org/deliverables.html

[11] A. Swindlehurst, B. Ottersten, R. Roy, and T. Kailath, "Multiple invariance ESPRIT," *IEEE Trans. Sig. Proc.*, vol. 40, no. 4, pp. 867–881, Apr. 1992.

[12] R. Roy and T. Kailath, "ESPRIT - Estimation of Signal Parameters via Rotational Invariance Techniques," *IEEE Trans on Acoustics, Speech, Signal Processing*, vol. 37, pp. 984–995, Jul 1989.

[13] L. Huang, T. Long, E. Mao, H. C. So, and S. Member, "MMSE-Based MDL Method for Accurate Source Number Estimation," *IEEE Signal Processing Letters*, vol. 16, no. 9, pp. 798–801, 2009.

[14] C. P. Mathews, M. Haardt, and M. D. Zoltowski, "Performance analysis of closed form, ESPRIT based 2-D Angle Estimator for rectangular arrays," *IEEE Sig. Proc. Letters*, 1996.