An Adaptive Parametric Prediction Method for Mobile MIMO Wireless Systems

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***Abstract*—In this paper, we investigate the prediction of mobile MIMO channels with varying multipath parameters. Based on the PAST algorithm, we propose a multidimensional adaptive ESPRIT approach for jointly tracking the evolution of the Doppler frequencies and spatial directions of arrival and departure of the propagation paths. Future states of the channel are predicted using the last estimate of the propagation parameters. We show via simulation that the proposed adaptive method outperforms existing static approaches with varying channel parameters. Our results indicate that the performance improvement from parameter tracking is dependent on the rate of variation of the underlying multipath parameters.**

***Index Terms*—channel prediction, wireless propagation, parameter estimation, multipath fading, PAST, ESPRIT, tracking**

I. Introduction

THERE are several instances in wireless communication where knowledge of the channel state information (CSI) at both the transmitter and receiver is useful. For example, transmit precoding techniques requiring accurate knowledge of the channel state information at the transmitter (CSIT) are often used to improve the performance of MIMO systems. In time diviision duplex (TDD) systems, CSIT can be obtained using reciprocity of the uplink and downlink channels. However, in frequency division duplex (FDD) systems, the transmitter relies on feebacks from the receiver for CSIT. As a result of the time–varying nature of the channel in mobile MIMO systems, the CSI often become outdated before its actual usage at the transmitter. Channel prediction has the potential to provide up–to–date CSI, and has been well studied for both SISO and MIMO systems (see e.g., [1]–[6] and the references therein).

Recently, schemes for the prediction of narrowband and wideband MIMO channels based on parametric radio channel (PRC) modeling were developed in [6]–[8]. These methods assume that the underlying propagation parameters are stationary over the region considered. However, as a result of movements in the scattering medium, these parameters may exhibit some variations in practice. There is therefore a need to track the spatial/temporal evolution of the parameters. Moreover, the computational complexity of the prediction schemes can be significantly reduced by eliminating the need for repeated eigenvalue decomposition and matrix inversions in the proposed method. A potential approach is to utilize low complexity subspace tracking schemes such as Projection Alternating Subspace Tracker (PAST) [9], [10] and Bi-iteration SVD [11]–[13]. Other methods utilize Bayesian schemes for recursive estimation such as the KF [14], EKF [15] and PF [16]. While there has been extensive literature on the prediction and tracking of MIMO channels using Bayesian approaches, particularly the KF in conjunction with AR models (see. e.g [17]–[20]), there exist few results on the application of these methods to the joint tracking of MIMO multipath parameters.

The focus of this paper is to investigate methods for jointly tracking the parameters of MIMO channels and channel extrapolation taking account for the temporal/spatial dynamics of the underlying propagation environment. Based on the PAST and ESPRIT algorithms, we derive a method for jointly tracking the parameters of the channel. The most current estimates of the parameters are used in the model for evaluating future values of the channel.

II. Model

A. Channel Model

We consider a mobile MIMO channel model defined as

$$\mathbf{H}(t) = \sum_{p=1}^{P(t)} \alpha_p(t)\mathbf{a}_{\mathrm{r}}(\mu_p^{\mathrm{r}}(t))\mathbf{a}_{\mathrm{t}}^T(\mu_p^{\mathrm{t}}(t))e^{j\omega_p(t)} \tag{1}$$

where $[\cdot]^T$ denotes non-conjugate transpose, $\alpha_p(t)$ and $\omega_p(t)$ are the time-varying complex amplitude and Doppler shift of the pth path. $\mu_p^{\mathrm{r}}(t)$ and $\mu_p^{\mathrm{t}}(t)$ are the spatial directions of arrival and departure, respectively. The vectors $\mathbf{a}_{\mathrm{r}}(\mu_p^{\mathrm{r}}(t))$ and $\mathbf{a}_{\mathrm{t}}(\mu_p^{\mathrm{t}}(t))$ are the receive and transmit array steering vectors. Assuming that the channel is sampled at interval T_{samp} ,(1) becomes

$$\mathbf{H}(k) = \sum_{p=1}^{P(k)} \alpha_p(k)\mathbf{a}_{\mathrm{r}}(\mu_p^{\mathrm{r}}(k))\mathbf{a}_{\mathrm{k}}^T(\mu_p^{\mathrm{t}}(k))e^{jk\eta_p(k)} \tag{2}$$

where k is the sample index, $\eta_p(k) = T_{\mathrm{samp}}\omega_p(k)$ is the normalized Doppler frequency. Each ray is characterized by the parameter set $\{\alpha_p(k), \mu_z^{\mathrm{r}}, \nu_p^{\mathrm{r}}(k), \mu_p^{\mathrm{t}}(k), \eta_p(k)\}$. Note that

(2) is valid for all array geometries. We consider a $N \times M$ MIMO system with ULA at both ends. For a N–element ULA, the array response vector is defined as[1]

$$\mathbf{a}(\mu_p) = \left[1, e^{j\mu_p}, \cdots, e^{j(N-1)\mu_p}\right]^T \tag{3}$$

We assume that K samples of the channel are known from estimation and denote the estimates as

$$\hat{\mathbf{H}}(k) = \mathbf{H}(k) + \mathbf{W}(k) \tag{4}$$

where $\mathbf{N}(k)$ is the additive complex Gaussian noise.

B. Modeling Temporal Variation of Channel Parameters

Now we will describe methods for modeling the dynamics of the parameters in (2). As described in [21], [22], the appearance of new scattering sources can be modeled as a homogeneous Poisson process with transition rate λ_{birth} and the lifetime of the scatterers can be described by an exponential random variable with mean $1/\lambda_{\text{life}}$. The number of active scatterers $P(t)$ at a given time instant is therefore a Poisson distributed random variable with mean $\mathbb{E}[P(t)] = \lambda_{\text{birth}}/\lambda_{\text{life}}]$. An illustration of the evolution of number of scatterers is shown in Fig. 1, where we have used $\lambda_{\text{birth}} = 10\lambda$ and $\lambda_{\text{life}} = 2\lambda$. The average number of paths is therefore, $\mathbb{E}[P(t)] = 5$.

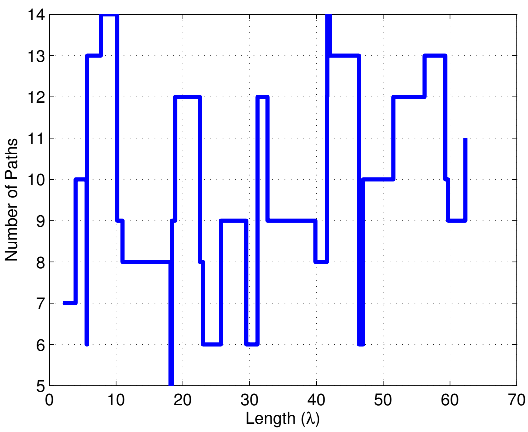


Fig. 1: Evolution of the number of active scatterers.

The dynamics of the structural parameters resulting from the movement of the mobile station and/or scatterers can be described using different models depending on the environment and the rate of motion. In our analysis, we consider two common models that are often used in time series analysis.

- First-order Autoregressive Model: The dynamics of a parameter θ can be defined using the AR(1) model:

$$\theta(k) = \beta_\theta \theta(k-1) + v(k) \tag{5}$$

  where β_θ controls the spatial/temporal variation of θ from a time instant to another and $v(k)$ is a Gaussian random variable with zero mean and variance σ_{v}^2. The AR(1) model was used in [23] to model time variation of path delays.
- Linear Advancement Model: An alternative approach to modeling the time variation allows the parameters to follow a straight line advancement thus

$$\theta_p(k) = \theta_p(0) + (k-1)T_{\text{samp}}\beta_\theta \tag{6}$$

  Here, β_θ defines the slope of the straight line and is typically determined by the rate of movements in the scattering medium. This approach was used in [24] for modeling delay variation in SISO channels where β_θ was defined in terms of the Doppler frequency as $\beta_\theta = \omega_p/\omega_c$.

[1]The definition of the spatial directions μ in terms angles of arrival/departure depends on the array orientation.

III. Adaptive MIMO Prediction

In this section, we present an adaptive method for prediction of narrowband MIMO channels with varying channel parameters. Unlike the existing approaches in [6]–[8], we relax the parameter stationarity assumptions in the adaptive prediction methods. Based on the PAST subspace tracker [9], [10], we derive a scheme for jointly tracking the structural parameters (i.e AOD, AOA and Doppler frequency) of the channel and predicting the CSI based on the evolution of the parameters. While it may be necessary to also allow the complex amplitudes of the propagation paths to be time-varying, we retain the assumption of constant amplitudes over a specified region.

A. Adaptive MEMCHAP

This section derives an adaptive Multidimensional ESPRIT based MIMO CHAnnel Predictor (MEMCHAP). The idea is to jointly track the parameters and use the parameter evolution to perform prediction. For simplicity we retain the assumption of quasi-stationary number of paths and complex weights and derive an adaptive multidimensional ESPRIT method for tracking the channel parameters. We also assume that the number of paths are known. A summary of the steps in the adaptive MEMCHAP are as follows.

- Adaptive Joint parameter estimation: Given the K noisy CSI estimates, the parameter set $\{\mu_p^{\text{r}}(k), \mu_p^{\text{r}}(k), \nu_p(k)\}_{p=1}^P$ are estimated for $k = 1, 2, \cdots, K$ in this step.
- Complex amplitude estimation: Using the estimated channel parameters at the Kth instant, the complex amplitudes are estimated via a least square approach.
- CSI prediction: As in the static approach, this stage involves extrapolation of the CSI based on the parameter estimates.

We now present a discussion of the adaptive estimation stage. For clarity, we begin with a semi-adaptive approach which involve repeated application of multidiemensional ESPRIT at every time instants.

1) Semi-Adaptive Joint Parameter Estimation: Let $\hat{\mathbf{h}}(k)$ be the vectorized form of $\hat{\mathbf{H}}(k)$. We assume that the parameters can be assumed constant over every K_c instants and define

$$\hat{\mathbf{d}}(i) = \begin{bmatrix} \hat{\mathbf{h}}((i-1)K_c+1) \\ \hat{\mathbf{h}}((i-1)K_c+2) \\ \vdots \\ \hat{\mathbf{h}}(iK_c) \end{bmatrix} ; i = 1, \cdots, I \tag{7}$$

where i is the new time instant at which parameters are to be estimated and $I = K/K_c$. The I data vectors correspond to vectorized version of I groups of K_c channel samples. The grouping combines the temporal and spatial channel structure into one dimension, so that 3D parameter estimation can be performed. As presented in [7], the central part of the 3D ESPRIT parameter estimation is the solution of invariance equations, thus

$$\hat{\mathbf{\Phi}}_{\mathrm{d}} = (\mathbf{J}_{\mathrm{d}2}\hat{\mathbf{E}}_{\mathrm{s}})^{\dagger}\mathbf{J}_{\mathrm{d}1}\hat{\mathbf{E}}_{\mathrm{s}} \tag{8}$$

$$\hat{\mathbf{\Phi}}_{\mathrm{r}} = (\mathbf{J}_{\mathrm{r}2}\hat{\mathbf{E}}_{\mathrm{s}})^{\dagger}\mathbf{J}_{\mathrm{r}1}\hat{\mathbf{E}}_{\mathrm{s}} \tag{9}$$

$$\hat{\mathbf{\Phi}}_{\mathrm{t}} = (\mathbf{J}_{\mathrm{t}2}\hat{\mathbf{E}}_{\mathrm{s}})^{\dagger}\mathbf{J}_{\mathrm{t}1}\hat{\mathbf{E}}_{\mathrm{s}} \tag{10}$$

where $(\cdot)^{\dagger}$ denotes the pseudo-inverse of the associated matrix, $\mathbf{E}_{\mathrm{s}}$ contains the eigenvectors of the covariance matrix corresponding to the signal subspace and $\mathbf{J}_{xi}; i = 1, 2$ are the rotational invariance selection matrices. The PAST algorithm presented in [10] can be applied to track the variations $\mathbf{E}_{\mathrm{s}}(i)$, thereby eliminating the need for repeated EVD. Let $V_{\mathrm{x}\ell}(i) = \mathbf{J}_{\mathrm{x}\ell}\hat{\mathbf{E}}_{\mathrm{s}}(i); \ell = 1, 2$, the semi-adaptive 3D ESPRIT can therefore be expressed as

$$\hat{\mathbf{\Phi}}_{\mathrm{x}}(i) = V_{\mathrm{x}1}^{\dagger}(i)V_{\mathrm{x}1}(i) \tag{11}$$

Again the MEVD can be applied to (11) to obtain automatically paired estimates. Denoting

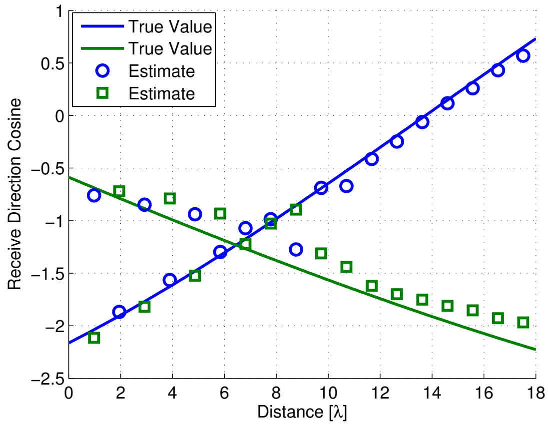
$$\begin{aligned} \hat{\mathbf{\Phi}}(i) &= \hat{\mathbf{\Phi}}_{\mathrm{r}}(i) + \hat{\mathbf{\Phi}}_{\mathrm{t}}(i) + \hat{\mathbf{\Phi}}_{\mathrm{d}}(i) \\ &= \mathbf{T}^{-1}\mathbf{\Lambda}\mathbf{T}, \end{aligned} \tag{12}$$

the parameters are obtained as

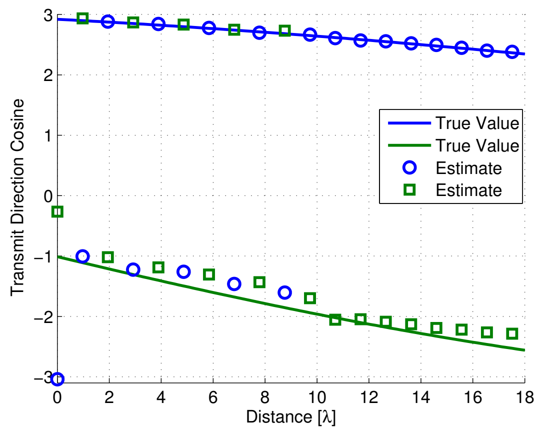
$$\begin{aligned} \hat{\boldsymbol{\mu}}^{\mathrm{r}}(i) &= \arg[\mathrm{diag}\{\mathbf{T}\hat{\mathbf{\Phi}}_{\mathrm{r}}(i)\mathbf{T}^{-1}\}] \\ \hat{\boldsymbol{\mu}}^{\mathrm{t}}(i) &= \arg[\mathrm{diag}\{\mathbf{T}\hat{\mathbf{\Phi}}_{\mathrm{t}}(i)\mathbf{T}^{-1}\}] \\ \hat{\boldsymbol{\nu}}(i) &= \arg[\mathrm{diag}\{\mathbf{T}\hat{\mathbf{\Phi}}_{\mathrm{d}}(i)\mathbf{T}^{-1}\}] \end{aligned} \tag{13}$$

The performance of the semi-adaptive joint parameter estimation and tracking is illustrated in Figs. 2, where we plot the true and estimated parameters. We consider a 2×2 narrowband MIMO channel with $P = 2$ paths and a mobile velocity $v = 50\,km/h$ at SNR$= 10\,$dB. We observe that the PAST based iterative estimation yields reasonable parameter tracking accuracy for all dimensions.

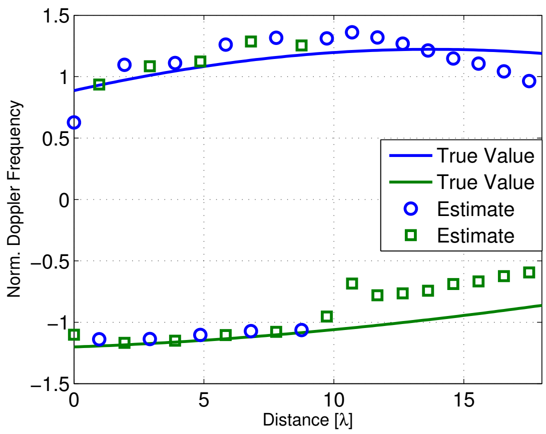
As in (11), this approach requires explicit computation of the matrices $\hat{\mathbf{\Phi}}_{\mathrm{x}}(i)$ at every time instant via a matrix inversion. As shown in [25] for one dimensional estimation, the computation can be eliminated by updating $\hat{\mathbf{\Phi}}_{\mathrm{x}}(i)$ recursively. A 3D extension of the adaptive ESPRIT method is presented in the next section.



(a) AOA



(b) AOD



(c) Doppler Shift

Fig. 2: Joint tracking of AOA, AOD and Doppler shifts at SNR$= 10\,$dB

2) Adaptive Joint Parameter Estimation: Consider the PAST subspace tracker in [10]. The signal eigenvector $\mathbf{E}_{\mathrm{s}}(i)$ is obtained via a rank-1 update, thus

$$\mathbf{E}_{\mathrm{s}}(i) = \mathbf{E}_{\mathrm{s}}(i-1) + \mathbf{e}(i)\mathbf{g}(i)^{H} \tag{14}$$

Analogously, the update of the matrices in 11 can be expressed as

$$\begin{aligned} V_{\mathrm{r}1}(i) &= V_{\mathrm{r}1}(i-1) + \mathbf{e}_{\mathrm{r}1}(i)\mathbf{g}(i)^H \\ V_{\mathrm{r}2}(i) &= V_{\mathrm{r}2}(i-1) + \mathbf{e}_{\mathrm{r}2}(i)\mathbf{g}(i)^H \\ V_{\mathrm{t}1}(i) &= V_{\mathrm{t}1}(i-1) + \mathbf{e}_{\mathrm{t}1}(i)\mathbf{g}(i)^H \\ V_{\mathrm{t}2}(i) &= V_{\mathrm{t}2}(i-1) + \mathbf{e}_{\mathrm{t}2}(i)\mathbf{g}(i)^H \\ V_{\mathrm{d}1}(i) &= V_{\mathrm{d}1}(i-1) + \mathbf{e}_{\mathrm{d}1}(i)\mathbf{g}(i)^H \\ V_{\mathrm{d}2}(i) &= V_{\mathrm{d}2}(i-1) + \mathbf{e}_{\mathrm{d}2}(i)\mathbf{g}(i)^H \end{aligned} \tag{15}$$

Our aim is to derive expression for recursively updating $\mathbf{\Phi}_{\mathrm{r}}$, $\mathbf{\Phi}_{\mathrm{t}}$ and $\mathbf{\Phi}_{\mathrm{d}}$. Consider the pseudo-inverse of $V_{\mathrm{r}1}(i)$ defined as

$$V_{\mathrm{r}1}^{\dagger}(i) = (V_{\mathrm{r}1}(i)^H V_{\mathrm{r}1}(i))^{-1} V_{\mathrm{r}1}(i)^H \tag{16}$$

Let

$$\mathbf{A}_{\mathrm{r}1}(i) = V_{\mathrm{r}1}(i)^H V_{\mathrm{r}1}(i), \tag{17}$$

and define

$$\mathbf{B}_{\mathrm{r}1}(i) = \mathbf{A}_{\mathrm{r}1}(i)^{-1} \tag{18}$$

such that (16) becomes

$$V_{\mathrm{r}1}^{\dagger}(i) = \mathbf{B}_{\mathrm{r}1}(i) V_{\mathrm{r}1}(i)^H \tag{19}$$

Substituting the corresponding update equation (15) into (17) yields

$$\begin{aligned} \mathbf{A}_{\mathrm{r}1}(i) &= V_{\mathrm{r}1}(i-1) + \mathbf{e}_{\mathrm{r}1}\mathbf{g}(i)^H)^H (V_{\mathrm{r}1}(i-1) + \mathbf{e}_{\mathrm{r}1}(i)\mathbf{g}(i)^H \\ &= V_{\mathrm{r}1}(i-1)^H V_{\mathrm{r}1}(i-1) + V_{\mathrm{r}1}(i-1)^H \mathbf{e}_{\mathrm{r}1}(i)\mathbf{g}(i)^H \\ &\quad + \mathbf{e}_{\mathrm{r}1}(i)^H \mathbf{g}(i) V_{\mathrm{r}1}(i-1) + (||\mathbf{e}_{\mathrm{r}1}(i)\mathbf{g}(i)||^2) \end{aligned} \tag{20}$$

Defining

$$\mathbf{C}_{\mathrm{r}1}(i) = \left[V_{\mathrm{r}1}(i-1)^H \mathbf{e}_{\mathrm{r}1}(i) \quad \mathbf{g}(i) \right], \tag{21}$$

$$\mathbf{D}_{\mathrm{r}1}(i) = \begin{bmatrix} 0 & 1 \\ 1 & ||\mathbf{e}_{\mathrm{r}1}(i)||^2 \end{bmatrix} \tag{22}$$

and using (17), (20) can be written as

$$\mathbf{A}_{\mathrm{r}1}(i) = \mathbf{A}_{\mathrm{r}1}(i-1) + \mathbf{C}_{\mathrm{r}1}(i)\mathbf{D}_{\mathrm{r}1}(i)\mathbf{C}_{\mathrm{r}1}(i)^H \tag{23}$$

Now substituting (23) into (18) yields

$$\mathbf{B}_{\mathrm{r}1}(i) = (\mathbf{A}_{\mathrm{r}1}(i-1) + \mathbf{C}_{\mathrm{r}1}(i)\mathbf{D}_{\mathrm{r}1}(i)\mathbf{C}_{\mathrm{r}1}(i)^H)^{-1} \tag{24}$$

Assuming that $\mathbf{A}_{\mathrm{r}1}(i-1)$, $\mathbf{C}_{\mathrm{r}1}(i)$ and $\mathbf{D}_{\mathrm{r}1}(i)$ are non-singular matrices, the matrix inversion in (24) can be expressed as [25]

$$\begin{aligned} \mathbf{B}_{\mathrm{r}1}(i) &= \mathbf{A}_{\mathrm{r}1}(i-1)^{-1} - \mathbf{A}_{\mathrm{r}1}(i-1)^{-1}\mathbf{C}_{\mathrm{r}1}(i) \left(\mathbf{D}_{\mathrm{r}1}(i)^{-1} \right. \\ &\quad \left. + \mathbf{C}_{\mathrm{r}1}(i)^H \mathbf{A}_{\mathrm{r}1}(i-1)^{-1}\mathbf{C}_{\mathrm{r}1}(i) \right)^{-1} \\ &\quad \times \mathbf{C}_{\mathrm{r}1}(i)^H \mathbf{A}_{\mathrm{r}1}(i-1)^{-1} \\ &= \mathbf{B}_{\mathrm{r}1}(i-1) - \mathbf{B}_{\mathrm{r}1}(i-1)\mathbf{C}_{\mathrm{r}1}(i) \left(\mathbf{D}_{\mathrm{r}1}(i)^{-1} \right. \\ &\quad \left. + \mathbf{C}_{\mathrm{r}1}(i)^H \mathbf{B}_{\mathrm{r}1}(i-1)\mathbf{C}_{\mathrm{r}1}(i) \right)^{-1} \\ &\quad \times \mathbf{C}_{\mathrm{r}1}(i)^H \mathbf{B}_{\mathrm{r}1}(i-1) \end{aligned} \tag{25}$$

Letting

$$\mathbf{\Xi}_{\mathrm{r}1}(i) = \mathbf{B}_{\mathrm{r}1}(i-1)\mathbf{C}_{\mathrm{r}1}(i), \tag{26}$$

and

$$\mathbf{\Sigma}_{\mathrm{r}1}(i) = \left(\mathbf{D}_{\mathrm{r}1}(i)^{-1} + \mathbf{\Xi}_{\mathrm{r}1}(i)\mathbf{C}_{\mathrm{r}1}(i) \right)^{-1}, \tag{27}$$

(25) reduces to

$$\mathbf{B}_{\mathrm{r}1}(i) = \mathbf{B}_{\mathrm{r}1}(i-1) - \mathbf{\Xi}_{\mathrm{r}1}(i)\mathbf{\Sigma}_{\mathrm{r}1}(i)\mathbf{\Xi}_{\mathrm{r}1}(i)^H \tag{28}$$

Substituting (28) into (19) yields

$$\begin{aligned} V_{\mathrm{r}1}^{\dagger}(i) &= \left(\mathbf{B}_{\mathrm{r}1}(i-1) - \mathbf{\Xi}_{\mathrm{r}1}(i)\mathbf{\Sigma}_{\mathrm{r}1}(i)\mathbf{\Xi}_{\mathrm{r}1}(i)^H \right) \\ &\quad \times \left(V_{\mathrm{r}1}(i-1) + \mathbf{e}_{\mathrm{r}1}(i)\mathbf{g}(i)^H \right) \end{aligned} \tag{29}$$

After straightforward mathematical simplifications, (29) becomes[2]

$$V_{\mathrm{r}1}^{\dagger}(i) = V_{\mathrm{r}1}^{\dagger}(i-1) + \mathbf{\Upsilon}(i)\mathbf{\Omega}(i)^H \tag{30}$$

where

$$\mathbf{\Upsilon}(i) = \mathbf{\Xi}_{\mathrm{r}1}(i)\mathbf{\Sigma}_{\mathrm{r}1}(i) \tag{31}$$

and

$$\mathbf{\Omega}(i) = [\mathbf{e}_{\mathrm{r}1}(i) \quad \mathbf{0}] - V_{\mathrm{r}1}(i-1)\mathbf{\Xi}_{\mathrm{r}1}(i) \tag{32}$$

Substituting (30) and the update equation for $V_{\mathrm{r}2}(i)$ in (15) into (11) gives

$$\begin{aligned} \hat{\mathbf{\Phi}}_{\mathrm{r}}(i) &= \left(V_{\mathrm{r}1}^{\dagger}(i-1) + \mathbf{\Upsilon}(i)\mathbf{\Omega}(i)^H \right) \left(V_{\mathrm{r}2}(i-1) + \mathbf{e}_{\mathrm{r}2}(i)\mathbf{g}(i)^H \right) \\ &= V_{\mathrm{r}1}^{\dagger}(i-1)V_{\mathrm{r}2}(i-1) + V_{\mathrm{r}1}^{\dagger}(i-1)\mathbf{e}_{\mathrm{r}2}(i)\mathbf{g}(i)^H \\ &\quad + \mathbf{\Upsilon}(i)\mathbf{\Omega}(i)^H V_{\mathrm{r}2}(i-1) + \mathbf{\Upsilon}(i)\mathbf{\Omega}(i)^H \mathbf{e}_{\mathrm{r}2}(i)\mathbf{g}(i)^H \\ &= \hat{\mathbf{\Phi}}_{\mathrm{r}}(i-1) + V_{\mathrm{r}1}^{\dagger}(i-1)\mathbf{e}_{\mathrm{r}2}(i)\mathbf{g}(i)^H + \mathbf{\Upsilon}(i)\mathbf{\Omega}(i)^H V_{\mathrm{r}2}(i) \end{aligned} \tag{33}$$

Defining

$$\mathbf{\Gamma}(i) = \left[V_{\mathrm{r}1}^{\dagger}(i-1)\mathbf{e}_{\mathrm{r}2}(i) \quad \mathbf{\Upsilon}(i) \right], \tag{34}$$

and

$$\mathbf{\Pi}(i) = [\mathbf{g}(i) \quad V_{\mathrm{r}2}(i)] \tag{35}$$

(33) can be written as

$$\hat{\mathbf{\Phi}}_{\mathrm{r}}(i) = \hat{\mathbf{\Phi}}_{\mathrm{r}}(i-1) + \mathbf{\Gamma}(i)\mathbf{\Pi}(i)^H \tag{36}$$

Expressions for updating $\hat{\mathbf{\Phi}}_{\mathrm{t}}(i)$ and $\hat{\mathbf{\Phi}}_{\mathrm{d}}(i)$ are obtained following a similar procedure. Again, we use (12) and (13) to extract the channel parameters.

3) CSI Prediction: Having estimated the time-varying channel parameters over the observation segment, the predicted CSI at a desired instant can be obtained by first extrapolating the parameters and then substituting into the model. Extrapolation of the channel parameters can be achieved by using either a linear or polynomial regression methods. However, there is an inherent problem of parameter association over time, making it difficult to apply any of the prediction methods. An alternative approach is to use the most current parameter estimates for evaluating future values of the CSI, thus

$$\tilde{\mathbf{H}}(k) = \sum_{p=1}^{P} \hat{\alpha}_p \mathbf{a}_{\mathrm{r}}(\mu_p^{\mathrm{r}}(K))\mathbf{a}_{\mathrm{t}}^T(\mu_p^{\mathrm{t}}(K))e^{jk\nu_p(K)} \tag{37}$$

for $k = K+1, K+2, \cdots$.

[2]A similar recursive update expression have been presented in [25] for the one-dimensional adaptive ESPRIT.

TABLE I: Simulation Parameters

Parameter	value
Carrier Frequency	2.1 GHz
Mobile Velocity	50 kp/h
Tx/Rx Antenna Conf.	ULA @ 1/2 λ spacing
Sampling Rate	10/λ
Variation Rate (β)	10^{-3}
Training Length	100

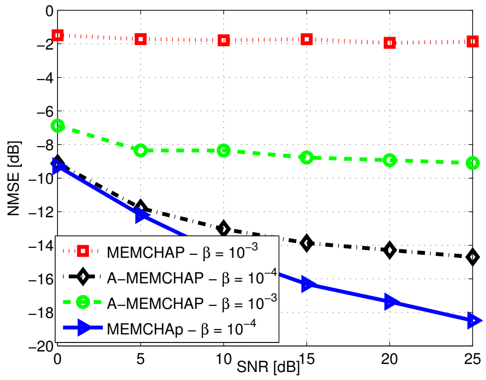


Fig. 3: NMSE of adaptive method at different variation rates.

IV. Simulation and Results

In this section, we evaluate the performance of the adaptive prediction method. We consider a 2×2 narrowband channel with parameters in Table I. Fig. 3 presents the prediction NMSE as a function of SNR at a prediction horizon of $0.1\,\lambda$. We observe that, with parameter variation rate of 10^{-3}, the PAST based adaptive method decreases the performance NMSE of DOD/DOA-MEMCHAP scheme by approximately 6 dB at all SNR values considered. However, both methods yield similar NMSE at low SNR for a slower rate of 10^{-4} with the DOD/DOA-MEMCHAP performing better at high SNR values. An explanation for this is that, while the adaptive method is able to overcome the degradation resulting from parameter variation the static method make better use of the measurements.

V. Conclusion

In this paper, we have investigated methods for jointly tracking the structural parameters of a narrowband MIMO channels based on a multidimensional extension of the adaptive ESPRIT scheme. The parameter tracking is achieved via a PAST subspace tracker. Simulation results shows existing approaches outperform the adaptive proposed method for stationary multipath parameters, the adaptive scheme offer improved prediction performance with increasing variation of the channel parameters. Validating the performance of the proposed scheme on measured channel will be considered in our future work.

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