Multipath Parameter Estimation and Channel Prediction for Wideband Mobile to Mobile Wireless Channel

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Abstract: In this paper, we investigate the estimation of multipath parameters and prediction of wideband multipath fading channels for mobile-to-mobile wireless communications. Based on a statistical model for mobile to mobile urban and sub-urban channels, we derive a parametrized model and utilize two-dimensional ESPRIT algorithm to jointly estimate the delay of arrival (DOA) and effective Doppler frequencies of the dominant paths from noisy channel observations. The parameter estimates are then used in the model to predict future states of the time-varying and frequency selective mobile-to-mobile channel. Simulations were performed to evaluate the performance of the prediction scheme and results show the potential for long range prediction in doubly selective mobile to mobile channels.

Key–Words: Multipath fading channels, wideband mobile-to-mobile channel, parameter estimation, ESPRIT, channel prediction

1 Introduction

Mobile-to-mobile (M2M) land wireless communication channels are channels that arise when both the transmit and receive stations are moving and are equipped with low elevation antenna. For example, a moving vehicle in a given place might communicate with one or more mobile vehicles in other places. These systems have several applications in traffic safety, rescue squads communication, congestion avoidance, etc. Recently, an international wireless standard, IEEE 802.11p, also referred to as Wireless Access in Vehicular Environment (WAVE) [1] has been developed. Based on the WiFi technology, this standard is proposed for both mobile to mobile and mobile to infrastructure traffic applications.

In order to cope with the challenge of developing and evaluating the performance of current and future mobile to mobile wireless communication systems, several research results have been published on the modelling of single input single output (SISO) mobile- to-mobile channels. In [2, 3], the statistical properties of narrowband SISO mobile to mobile multipath fading channel was investigated based on models for the channel impulse response and transfer function. The authors of [4] present results on the temporal correlation properties and Doppler power spectral characteristics in 3D propagation environments. These results have shown that the fading and statistics of mobile to mobile channel differ significantly from classical fixed to mobile channel where the transmitter is stationary. Channel models for wideband mobile to mobile wireless propagation have also been reported (see e.g [5],[6] and the references therein).

In this paper, we investigate multipath parameter estimation and channel state prediction of doubly selective mobile to mobile channel fading channels. It is well known from channel prediction studies for fixed to mobile channels [7, 8, 9, 10, 11] that channel prediction offer significant benefit in mitigating against performance loss from multipath fading and improving the system performance by providing both the transmitter and receiver with accurate prediction of the channel impulse response. We believed that this fact, coupled with the faster variation exhibited by mobile to mobile channels, make channel prediction an important technique for mobile-to mobile channels. Based on statistical model of the wideband mobile to mobile channel, we derive a model to jointly estimate the effective Doppler frequencies and delays using super resolution subspace based Estimation of Signal parameters via Rotational Invariance Techniques (ESPRIT) algorithm and applying the parameters estimates for predicting the fading mobile to mobile channel impulse response in time and frequency.

The rest of this paper is organized as follows. In Section 2, we present the statistical channel model for mobile to mobile systems and derive a simple parametrized model for parameter estimation and prediction in wideband doubly selective propagation scenarios. In Section 3, we describe the 2D ESPRIT based approach for jointly estimating the delays and effective Doppler frequency along with the least square complex amplitude estimation. In Section 4, we present the parametric prediction based on the estimated parameters. Section 5 present some results from the numerical simulations. Finally, conclusions are drawn in Section 6.

2 Channel Models

This section present the Rayleigh fading doubly selective SISO M2M channel considered in this paper along with a reduced parametrized model for wideband mobile to mobile parameter estimation and prediction.

2.1 Wideband Mobile-to-Mobile Channel Model

We consider a wideband SISO mobile to mobile wireless communication system. Figure 1 shows an illustration of the mobile to mobile propagation in typical urban and suburban environments. Both the transmitter and receiver are assumed to be moving with velocities V_T and V_R, respectively. It is further assumed that both the transmitter and receiver are equipped with low elevation omnidirectional antennas. As shown in Fig. 1, a signal will arrive at the receiver via scattering and reflection in all directions, by local scatterers/reflectors around the transmitter and receiver and all distant scattering mediums. It is also assumed that the line-of-sight (LOS) component is obstructed by obstacles between the transmitter and receiver. The complex Rayleigh faded channel is thus modelled as [2, 3]

$$h(t,\tau) = \sum_{k=1}^{K} \alpha_k \exp(j[(\omega_{Tk}+\omega_{Rk})t+\phi_k])\delta(\tau-\tau_k) \quad (1)$$

where α_k is the Rayleigh distributed amplitude for the kth path, ϕ_k is the kth path phase parameter assumed to be uniformly distributed on $(0, 2\pi)$, τ_k is the delay of the kth paths and K is the number of propagation paths. ω_{Tk} and ω_{Rk} are the radian Doppler shifts resulting for the mobility of the transmitter and receiver, respectively and are given by

$$\omega_{Tk} = \frac{2\pi}{\lambda} V_T \cos(\theta_{Tk}) \quad (2)$$

$$\omega_{Rk} = \frac{2\pi}{\lambda} V_R \cos(\theta_{Rk}) \quad (3)$$

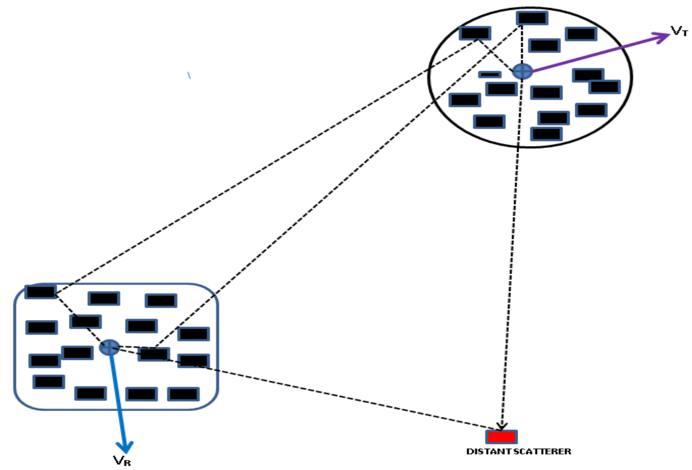

Figure 1: Mobile to Mobile Wireless Transmission. The propagation channel is characterized by local scatterers around both the transmitter and receiver and distant scattering sources.

where θ_{Tk} and θ_{Rk} are random angles of departure at the transmitter and angles of arrival of the kth path respectively. λ is the carrier wavelength. As can be seen from (1), the receive signal will experience Doppler frequency shifts due to the mobility of both the transmitter and receiver. The dual mobility in mobile to mobile channels result in more rapid temporal variation of the fading envelope when compared with classical mobile cellular system with fixed transmitter. It should be noted that the sum of sinusoids model commonly used for SISO prediction studies (see e.g [12, 8, 10, 13]) is a special case of (1) with $V_T = 0$.

2.2 Parametrized Model

In order to reduce the mobile-to-mobile channel prediction problem to a sinusoidal parameter estimation problem, we denote

$$\beta_k = \alpha_k \exp(j\phi_k) \quad (4)$$

and

$$\begin{aligned}\omega_k &= \omega_{Tk} + \omega_{Rk} \\ &= \frac{2\pi}{\lambda}(V_T \cos(\theta_{Tk}) + V_R \cos(\theta_{Rk})) \quad (5)\end{aligned}$$

We will henceforth, refer to β_k as the complex amplitude of the kth path and ω_k as the effective radian Doppler frequency. Substituting (4) and (5) into (1), we obtain

$$h(t,\tau) = \sum_{k=1}^{K} \beta_k \exp(j\omega_k t)\delta(\tau-\tau_k) \quad (6)$$

The parameters β_k and ω_k are assumed constant over the region of interest[1] The frequency response of the channel is obtained by taken the Fourier transform of (6) as

$$H(t,f) = \sum_{k=1}^{K} \beta_k \exp(j\omega_k t - j2\pi f \tau_k) \tag{7}$$

where f denotes the frequency variable. We assumed that L time domain samples and S frequency domain samples of the channel are known either by transmitting known pilot sequences or from measurement. In practice, the estimated or measured channel will be imperfect due to the effects of background noise and interference. We therefore model the known channel at time t and frequency f as

$$\hat{H}(t,f) = H(t,f) + z(t,f) \tag{8}$$

where $H(t,f)$ is the actual channel and $z(t,f)$ is a random variable that accounts for the effect of noise and interference assumed to be zero mean Gaussian with variance σ_z^2.

3 Parameter Acquisition

In the previous section, we present the doubly selective channel model for mobile to mobile wireless propagation along with a parametrized model for parameter extraction and channel prediction. In this section, we present the 2D ESPRIT based parameter estimation scheme for jointly estimating the delay and Doppler shifts of the multiple paths.

3.1 Joint Doppler Frequency and Delay Estimation

Assuming that the temporal sampling interval is Δ_t and that the frequency samples are spaced Δ_f apart, the sampled frequency response can be written as

$$H(\ell,s) = \sum_{k=1}^{K} \beta_k \exp(j\ell\omega_k \Delta_t - j2\pi s \Delta_f \tau_k) \tag{9}$$

where ℓ and s are the time and frequency indices respectively. Let $\hat{\mathbf{h}}(s) = [H(1,s), H(2,s), \cdots, H(L,s)]^T \in \mathbb{C}^{L\times 1}$ be a vector containing the L frequency response with frequency index s. $\hat{\mathbf{h}}(s)$ corresponds to a vector containing all the temporal samples of the frequency response of the sth sub-carrier. We collect the frequency response for all subcarriers into a vector as

$$\hat{\mathbf{h}} = \begin{bmatrix} \hat{\mathbf{h}}(0) \\ \hat{\mathbf{h}}(1) \\ \vdots \\ \hat{\mathbf{h}}(S-1) \end{bmatrix} \in \mathbb{C}^{LS\times 1}, \tag{10}$$

Using (5) and (6), the data vector in (10) can be modelled as

$$\hat{\mathbf{h}} = \mathbf{F}\boldsymbol{\beta} + \mathbf{z} \tag{11}$$

where

$$\mathbf{F} = \mathbf{G} \diamond U \tag{12}$$

and

$$\boldsymbol{\beta} = [\beta_1, \beta_2, \cdots, \beta_K]^T \tag{13}$$

$[\cdot]^T$ denotes the transpose operation, $\diamond$ denotes the Khatri-Rao column-wise Kronecker product and $\mathbf{z} \in \mathbb{C}^{LS\times 1}$ is the noise vector. The matrices $\mathbf{G}$ and $\mathbf{U}$ in (9) are defined as

$$\mathbf{G} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ g_1 & g_2 & \cdots & g_K \\ \vdots & \vdots & \ddots & \vdots \\ g_1^{L-1} & g_2^{L-1} & \cdots & g_K^{L-1} \end{bmatrix} \in \mathbb{C}^{L\times K}, \tag{14}$$

and

$$\mathbf{U} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ u_1 & u_2 & \cdots & u_K \\ \vdots & \vdots & \ddots & \vdots \\ u_1^{S-1} & u_2^{S-1} & \cdots & u_K^{S-1} \end{bmatrix} \in \mathbb{C}^{S\times K}, \tag{15}$$

$g_k = \exp(j\omega_k \Delta t)$ and $u_k = \exp(-j2\pi\Delta_f \tau_k)$. Let $\mathbf{F}_{\omega 1}$, $\mathbf{F}_{\omega 2}$, $\mathbf{F}_{\tau 1}$ and $F_{\tau 2}$ be matrices selected from $\mathbf{F}$ such that

$$\begin{aligned} \mathbf{F}_{\omega 1}\boldsymbol{\gamma}_1 &= \mathbf{F}_{\omega 2} \\ \mathbf{F}_{\tau 1}\boldsymbol{\gamma}_2 &= \mathbf{F}_{\tau 2} \end{aligned} \tag{16}$$

where

$$\boldsymbol{\gamma}_1 = \begin{bmatrix} g_1 & 0 & \cdots & 0 \\ 0 & g_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & g_K \end{bmatrix} \in \mathbb{K} \times \mathbb{K} \tag{17}$$

and

$$\boldsymbol{\gamma}_2 = \begin{bmatrix} u_1 & 0 & \cdots & 0 \\ 0 & u_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & u_K \end{bmatrix} \in \mathbb{K} \times \mathbb{K} \tag{18}$$

[1]This assumption has been shown to be valid for a horizon of $T_{valid} = \sqrt{\frac{cr_{min}}{3f_c v^2}}$ in fixed to mobile systems [12]. r_{min} denotes the distance between the mobile and the nearest scatterer/reflector. Further studies may be required to develop similar analytical expression for mobile-to-mobile channels. This is however, beyond the scope of this work.

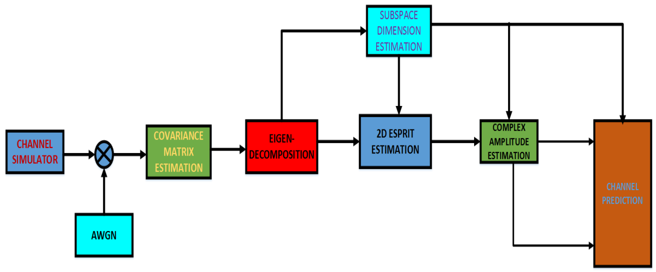

Figure 2: Detailed block diagram of the proposed mobile to mobile prediction algorithm. The channel simulator generates the channel impulse response using the multipath parameters and propagation scenario. The AWGN generator adds a complex Gaussian noise with zero mean to the channel and the covariance matrix is then estimated. The next block perform eigendecomposition of the covariance matrix and input the eigenvalues and eigenvectors to the subspace dimension and 2D ESPRIT estimation blocks where the number of sources and channel parameters are estimated. The complex amplitude is then estimated using the estimated parameters. Finally, the prediction block extrapolates the channel using a specified model and the parameter estimates.

We define the following selection matrices

$$\begin{aligned} J_{1\omega} &= \begin{bmatrix}\mathbf{I}_{(L-1)} & \mathbf{0}_{(\mathbf{L-1})}\end{bmatrix} & J_{\omega 1} &= J_{1\omega} \otimes \mathbf{I}_S \\ J_{2\omega} &= \begin{bmatrix}\mathbf{0}_{(L-1)} & \mathbf{I}_{(\mathbf{L-1})}\end{bmatrix} & J_{\omega 2} &= J_{2\omega} \otimes \mathbf{I}_S \\ J_{1\tau} &= \begin{bmatrix}\mathbf{I}_{(S-1)} & \mathbf{0}_{(\mathbf{S-1})}\end{bmatrix} & J_{\tau 1} &= \mathbf{I}_L \otimes J_{1\tau} \\ J_{2\tau} &= \begin{bmatrix}\mathbf{0}_{(S-1)} & \mathbf{I}_{(\mathbf{S-1})}\end{bmatrix} & J_{\tau 2} &= \mathbf{I}_L \otimes J_{2\tau} \end{aligned} \tag{19}$$

The matrices in (16) can then be obtained from $\mathbf{F}$ using

$$\begin{aligned} \mathbf{F}_{\omega 1} &= J_{\omega 1}\mathbf{F} \\ \mathbf{F}_{\omega 2} &= J_{\omega 2}\mathbf{F} \\ \mathbf{F}_{\tau 1} &= J_{\tau 1}\mathbf{F} \\ \mathbf{F}_{\tau 2} &= J_{\tau 2}\mathbf{F} \end{aligned} \tag{20}$$

Assuming that $\mathbf{F}$ is known, (16) can be solved for the delays and effective Doppler frequencies. However, $\mathbf{F}$ is unknown in practice but span the signal subspace. We form an Hankel matrix from the data in (10) as

$$\hat{\mathbf{H}} = \begin{bmatrix} \hat{\mathbf{h}}(0) & \hat{\mathbf{h}}(1) & \cdots & \hat{\mathbf{h}}(P-1) \\ \hat{\mathbf{h}}(1) & \hat{\mathbf{h}}(2) & \cdots & \hat{\mathbf{h}}(P) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\mathbf{h}}(Q-1) & \hat{\mathbf{h}}(Q) & \cdots & \hat{\mathbf{h}}(S-1) \end{bmatrix} \tag{21}$$

where $P+Q=S+1$. The size of the Hankel matrix $\hat{\mathbf{H}}$ is limited by the number of time and frequency samples of the channel available from the estimation stage. The choice of the Hankel size parameters is thus a compromise between accuracy, identifiability and complexity. In order to have a sufficiently large correlation matrix, we compute P using

$$P = \left\lceil \frac{2}{3}S \right\rceil \tag{22}$$

where $\lceil A \rceil$ denotes the smallest integer greater than A. The time-frequency covariance matrix is then estimated using

$$\hat{\mathbf{R}} = \frac{HH\dagger}{P} \tag{23}$$

where $\dagger$ denotes Hermitian transpose. The signal subspace matrix can be obtained from the singular value decomposition (SVD) or eigen value decomposition (EVD) of $\hat{\mathbf{R}}$. Based on the estimated eigenvalues, the number of dominant paths can be estimated using the Minimum Description length (MDL) criterion [14]. A modified version of MDL referred to as Minimum Mean Squared Error (MMSE) based Minimum Description Length (MDL) criterion is used for the estimation [15]

$$\hat{K} = \arg \min_{i=1,\cdots,QL-1} \mathrm{MMDL}(i) \tag{24}$$

where $\mathrm{MMDL}(i)$ is given by

$$\mathrm{MMDL}(i) = P\log(\lambda_i) + \frac{1}{2}(i^2+i)\log P \tag{25}$$

$\lambda_i; i = 1, 2, \cdots, QL$ are the eigenvalues of $\hat{\mathbf{R}}$. Once K has been estimated, the signal subspace matrix $\hat{\mathbf{V}}_s$ is obtained from the $\hat{K}$ eigenvectors corresponding to the largest eigenvalues of $\hat{\mathbf{R}}$. Similar to (16), we form the following invariance equation

$$\begin{aligned} \mathbf{V}_{s\omega 1}\mathbf{\Phi}_1 &= \mathbf{V}_{s\omega 2} \\ \mathbf{V}_{s\tau 1}\mathbf{\Phi}_2 &= \mathbf{V}_{s\tau 2} \end{aligned} \tag{26}$$

where $\mathbf{\Phi}_1$ and $\mathbf{\Phi}_2$ are subspace rotated versions of $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_2$ respectively. It has been shown that $\mathbf{\Phi}_1$ and $\mathbf{\Phi}_2$ [16, 17] can be used to estimate the Doppler frequencies and delays. Equation (26) can be solved in the least square sense to obtain

$$\begin{aligned} \mathbf{\Phi}_1 &= (\hat{\mathbf{V}}_{s\omega 1}^{\dagger}\hat{\mathbf{V}}_{s\omega 1})^{-1}\hat{\mathbf{V}}_{s\omega 1}^{\dagger}\hat{\mathbf{V}}_{s\omega 2} \\ \mathbf{\Phi}_2 &= (\hat{\mathbf{V}}_{s\tau 1}^{\dagger}\hat{\mathbf{V}}_{s\tau 1})^{-1}\hat{\mathbf{V}}_{s\tau 1}^{\dagger}\hat{\mathbf{V}}_{s\tau 2} \end{aligned} \tag{27}$$

The parameter estimates are then obtained as

$$\begin{aligned} \hat{\boldsymbol{\omega}} &= \frac{\arg(\mathrm{eig}[\mathbf{\Phi}_1])}{\Delta t} \\ \hat{\boldsymbol{\tau}} &= -\frac{\arg(\mathrm{eig}[\mathbf{\Phi}_2])}{2\pi\Delta f} \end{aligned} \tag{28}$$

where $\arg(\cdot)$ denotes the phase angle of the associated complex number on $(0, 2\pi]$ and $\mathrm{eig}[.]$ computes the eigenvalues of the associated matrix.

Table 1: Simulation Parameters

Parameter	Value
Carrier Frequency	2.0 GHz
Number of Subcarriers	128
Bandwidth	20MHz
Transmitter Velocity	5 Kmph
Training Length	$30-70$
Receiver Velocity	50 Kmph
Angle of Departure	$\mathbb{U}[-\pi, \pi]$
Angle of Arrival	$\mathbb{U}[-\pi, \pi)$
Sampling Interval	1 ms
Number of Paths	5 - 30
Amplitude	$\mathbb{N}(0, 1)$
Phase	$\mathbb{U}(0, 2\pi)$

3.2 Complex Amplitude Estimation

Once the effective Doppler frequencies and delays of arrival have been estimated, the complex amplitudes of the $\hat{K}$ dominant paths are computed via a solution of the set of linear equations in (11) for the first subcarrier. We solve the equations using regularized least squares as

$$\hat{\boldsymbol{\beta}} = (\mathbf{G}^{\dagger}\mathbf{G} + \nu\mathbf{I})^{-1}\mathbf{G}^{\dagger}\hat{\mathbf{h}}(0) \tag{29}$$

where ν is a regularization parameter that is introduced to minimize the effects of errors in $\mathbf{G}$ on the predictor performance. We chose ν empirically in our simulations.

4 Channel Prediction

Using the estimated channel parameters, the mobile to mobile channel impulse response can be predicted into the future by substituting the parameters into (5) for the desired time instant. The predicted channel is given by

$$\tilde{H}(\ell+\Delta, s+\delta) = \sum_{k=1}^{\hat{K}} \hat{\beta}_k \exp(j(\ell+\Delta)\omega_k\Delta_t - j2\pi(s+\delta)\Delta_f\tau_k) \tag{30}$$

where Δ denotes the number of temporal samples ahead to be predicted.

5 Numerical Simulations

In this section, we analyse the performance of the mobile to mobile parametric channel prediction algorithm proposed in this paper. The prediction error of the algorithm is evaluated using the normalized mean squared error (NMSE) criterion[2]

$$\begin{aligned}\text{NMSE}(\tau) &= \frac{\mathbb{E}[|\tilde{h}(\tau) - h(\tau)|^2]}{\mathbb{E}[|h(\tau)|^2]} \\ &\approx \frac{1}{M}\sum_{m=1}^{M} \frac{\sum_{z=1}^{Z} |\hat{h}(\tau) - h(\tau)|^2}{\sum_{z=1}^{Z} |h(\tau)|^2}\end{aligned} \tag{31}$$

where M is the number of snapshots. The wideband doubly selective time-varying channel is generated using the parameters in Table 1 (except where otherwise stated). In Figure 3, we plot the amplitude (i.e gain) of the frequency selective mobile to mobile channel. It shows that the channel exhibits both time and frequency variation. A similar observation is made in Fig. 4 where we plot the phase (in radians) of the mobile to mobile channel. Compare to previous results on fixed to mobile cellular systems, the temporal variation of the mobile to mobile channel is relatively faster. This is due to the additional Doppler spread introduced by the mobility of the transmitter. This agreed with observations in [2, 3] where it was also shown that mobile to mobile channels has significantly different statistics. In Figure 5, we present a plot of the actual and estimated delays and effective Doppler frequencies for one realization of the channel at SNR=20dB. As can be observed from the plot, the algorithm produces very accurate estimates of the channel parameters for all the paths present in the channel. Figure 6 shows a plot of the actual and predicted channel gains at SNR=20dB for prediction horizon up to 0.5s. We observe the our algorithm is able to track the amplitude of the channel accurately even for such long prediction range. This is a tremendous improvement over previously reported methods for fixed to mobile systems. Similarly, figure 7 presents the actual and predicted phase of the channel for the same prediction horizon. We observed that the phase angle prediction is also very accurate except for a single instant where the algorithm produces some errors in the phase. A typical variation of the channel across the frequency samples is shown in figure 8 where we plot the channel amplitude versus frequency values. We observe that our algorithm is also able to predict the channel accurately for all frequency instants. This is expected, since the algorithm utilizes both the temporal and frequency statistics of the channel to aid the prediction. Finally, we present the normalized mean square error versus prediction length for different SNR values in Figure 9. We observe that the prediction error increases with increasing prediction length and decreases with increasing SNR. A plausible explanation for this is that as you travel away from the prediction point, it becomes more difficult to predict the channel accurately and the parameter estimation accuracy improves

[2]The NMSE in our simulation is averaged over all the subcarriers in the wideband system.

with increasing SNR.

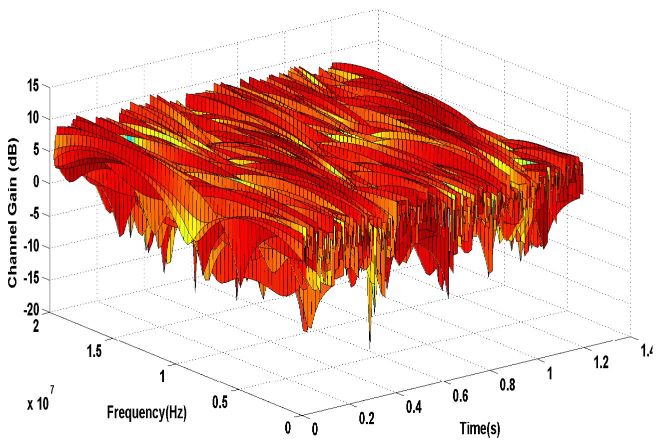

Figure 3: Amplitude of wideband mobile to mobile channel showing temporal and frequency variations of the channel.

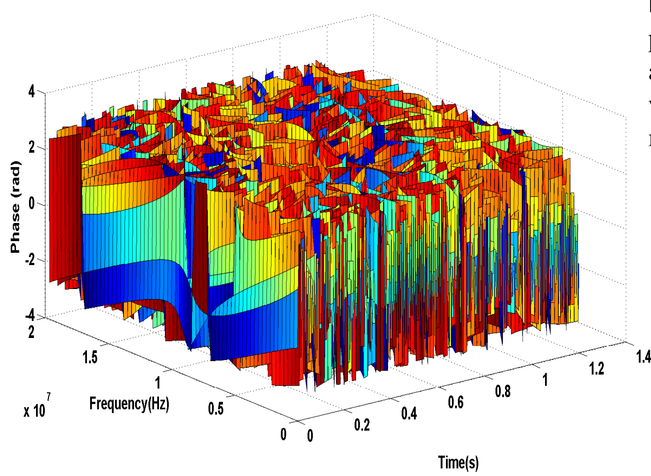

Figure 4: Phase plot of a realization of the doubly selective mobile to mobile channel.

6 Conclusion

In this paper, we have proposed a novel algorithm for the multipath parameter estimation and channel state prediction for doubly selective mobile to mobile wireless channel. Using the classical statistical model for mobile to mobile propagation, we derive a parametric model for jointly estimating the delay of arrival and effective Doppler frequencies of the multipath channel. An ESPRIT based approach is proposed for the joint parameter extraction and the estimated parameters were used to extrapolate the channel in

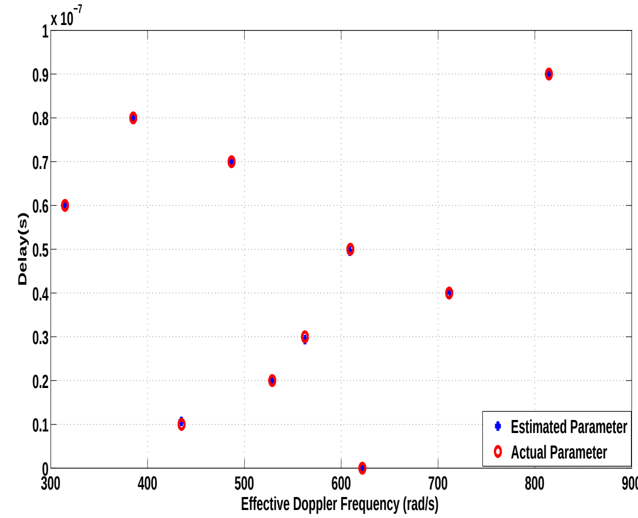

Figure 5: Actual and estimated delays and effective Doppler frequencies for a wideband mobile to mobile channel with ten propagation paths at SNR $= 10\,$dB.

both time and frequency. Simulation results show that the proposed scheme can high accurate parameter estimation and long range prediction of the fading channel. Future work will analyse the performance of the algorithm using measured channel data and system level simulations.

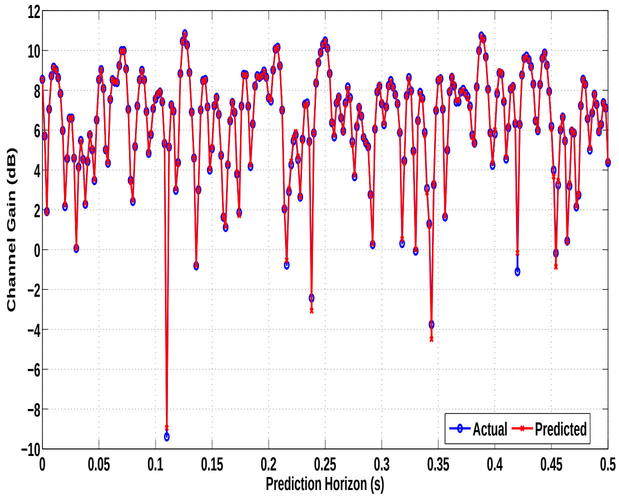

Figure 6: Actual and predicted channel gain for the 10th subcarrier of a wideband mobile to mobile channel at $\mathrm{SNR} = 20\,\mathrm{dB}$ using 100 known samples of the channel for predictor initialization.

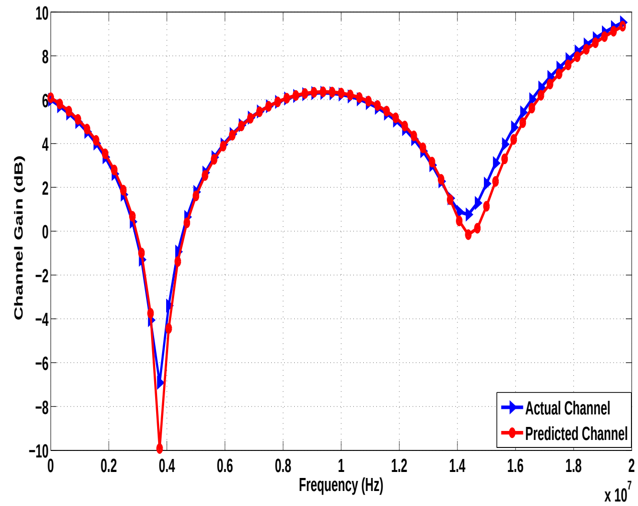

Figure 8: Actual and predicted frequency variation of a wideband mobile to mobile channel at the 580th symbol duration at $\mathrm{SNR} = 20\,dB$.

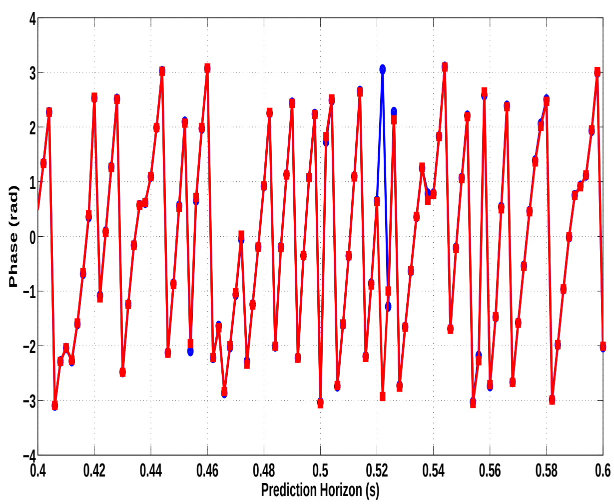

Figure 7: Actual and predicted phase for the 10th subcarrier of a wideband mobile to mobile channel at $\mathrm{SNR} = 20\,\mathrm{dB}$ using 100 known samples of the channel for predictor initialization.

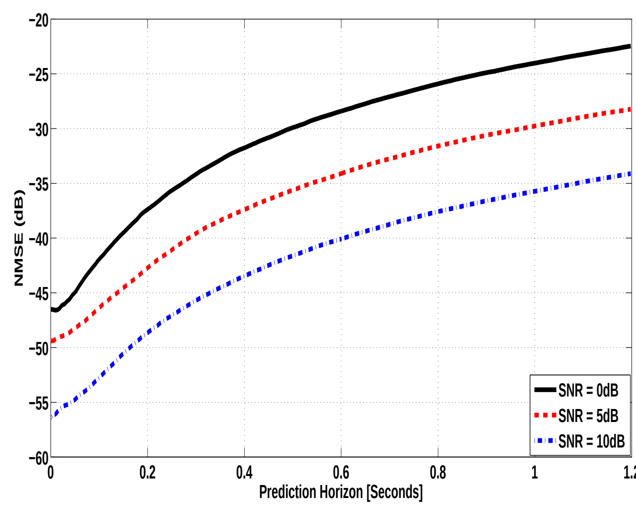

Figure 9: Normalized mean square error versus prediction horizon (s) for wideband mobile to mobile channel prediction using the proposed algorithm at SNR= $[0, 5, 10]$dB.

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