MODELS AND PREDICTIONS OF SCATTERED RADIO WAVES ON ROUGH SURFACES

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ABSTRACT

Scattering of radio waves on rough surfaces is investigated using ray tracing techniques, which results in a sinusoidal model with time varying amplitudes. An AR(d) model with nonzero mean is proposed to characterize and predict the time variation of the amplitudes. A covariance sequence based method is proposed to estimate the autoregressive coefficients from the channel observations. An adaptive channel predictor using a Kalman filter is proposed to predict the complex amplitudes of the scattering signal. The proposed method outperforms other sinusoidal modeling based channel predictors and Linear Predictors with single scattering scenarios in simulations.

Index Terms - Adaptive Kalman filtering, Wave propagation, Rayleigh channels, Prediction methods

1. INTRODUCTION

Reflections and scattering of radio waves on different physical objects provide the multipath propagation environments in wireless communications. A propagation path via reflection on a smooth surface results in a constant Doppler frequency component in a Rayleigh fading channel. With p specular reflection paths, the channel $h(t)$ could be modeled as

$$h(t) = \sum_{i=1}^{p} s_i e^{j\omega_i t}, \qquad (1)$$

where s_i and ω_i are the complex amplitude and the Doppler frequency respectively. In this paper, j is used as both subscript and $\sqrt{-1}$ when there is no risk for notation confusion. The estimated channel is

$$y(t) \quad = \quad h(t) + e(t), \qquad (2)$$

where $e(t)$ is the estimation error with pdf, $\mathcal{CN}(0, \sigma_e^2)$. In the following discussion, we assume that $\mathbf{y} = [y(t), y(t-1), \cdots, y(t-N+1)]^T$ is observed, where ^{T} is transpose operation. Such a model with constant parameters was adopted in channel predictors based on sinusoidal modeling in [1]-[4]. But it was observed that these model parameters experience slow time evolution in measurement data [5]. This leads to significant degradation of the performance comparing to those in simulations.

Efforts have been made to alleviate the influence of the time varying model parameters, i.e. [4], where the complex amplitudes, $\mathbf{s} = [s_0, s_1, \cdots, s_p]^T$, and the frequencies, $\boldsymbol{\omega} = [\omega_0, \omega_1, \cdots, \omega_p]^T$, of the sinusoidal signals were modeled as Gaussian random variables with pdf, $\mathcal{CN}(\mathbf{0}, \sigma_\mathbf{s}^\mathbf{2}\mathbf{I_p})$, and $\mathcal{N}(\hat{\boldsymbol{\omega}}, \sigma_\omega^2 \mathbf{I}_p)$ respectively. The vector $\hat{\boldsymbol{\omega}}$ is the estimated Doppler frequencies. This extension helps to improve the performance of predictors based on sinusoidal modeling, but the relative performances between Linear Predictors (LP) and these methods does not agree by using simulation data and measurement data.

In this paper, a model of scattering on rough surface is proposed, which results in a sinusoidal model with constant frequency and time varying amplitudes. Such a model is more suitable to generate Rayleigh fading channels in related studies in wireless communications, such as MIMO channel modeling, channel prediction, and beamforming etc. To characterize the dynamics of the amplitudes, an AR(d) model with nonzero mean is proposed. To be able to track the time varying amplitudes, an adaptive channel predictor using a Kalman filter is proposed. Its performance is evaluated using simulation data in single scattering cluster scenarios. Extensive performance evaluation in multiple scattering clusters and measurement data is kept for future work.

2. MODELS OF SCATTERING ON ROUGH SURFACES

In practice, it is most likely that the reflection of radio wave is on a rough plane, where the reflected wave becomes scattered from a large number of positions on the surface. The degree of the scattering depends on the incidence angle and on the roughness of the surface in comparison to the wave length, λ. So the radio channel scattered on the i^{th} rough surface can be approximated as

$$h_i(t) = \sum_{j=1}^{q_i} s_i' r_{i,j} e^{jkl_{i,j}(t)}, \quad (3)$$

where q_i is the number of reflection positions in the scattering area, s_i' is the amplitude of the incident wave before reflection, $l_{i,j}(t)$ is the path length and is a function of time, and $k = 2\pi/\lambda$ is the wave number, $r_{i,j}$ is termed *reflection coefficient* , which depends on the impedance of the media and the incident angle. Note that the reflection coefficients at different positions are assumed to be identical over time and over the scattering surface in (3), which results in identical reflected amplitude, $s_i'' = s_i' r_{i,j}$. To keep the average power of $h_i(t)$ be the same as $\|s_i\|^2$,let $s_i'' = s_i/\sqrt{q_i}$, and the simplified model becomes

$$h_i(t) = \sum_{j=1}^{q_i} \frac{s_i}{\sqrt{q_i}} e^{jkl_{i,j}(t)}. \quad (4)$$

Define $(x_{i,j}, y_{i,j})$ be the coordinate of the j^{th} reflection position in the i^{th} scattering surface, and the center of gravity of the i^{th} scattering surface as $(x_{i,c}, y_{i,c})$, where $x_{i,c} = \sum_{j=1}^{q_i} x_{i,j}/q_i$, and $y_{i,c} = \sum_{j=1}^{q_i} y_{i,j}/q_i$. Let $l_{i,c}(t)$ be the length of the propagation path via $(x_{i,c}, y_{i,c})$, and

$$\Delta l_{i,j}(t) = l_{i,j}(t) - l_{i,c}(t). \quad (5)$$

Then, the model in (4) becomes

$$\begin{aligned} h_i(t) &= \sum_{j=1}^{q_i} \frac{s_i}{\sqrt{q_i}} e^{jk(l_{i,c}(t)+\Delta l_{i,j}(t))}, \\ &= \left(\frac{s_i}{\sqrt{q_i}} \sum_{j=1}^{q_i} e^{jk\Delta l_{i,j}(t)} \right) e^{jkl_{i,c}(t)}, \\ &= s_i(t) e^{jkl_{i,c}(t)}, \end{aligned} \quad (6)$$

where we assume $l_{i,c}(t)$ varies linearly with time (i.e. constant speed), and $\Delta l_{i,j}(t)$ is assumed to be uniform distributed in $[-\gamma\lambda, \gamma\lambda]$. The parameter γ defines the size/roughness of the scattering surface. The larger γ is, the larger/rougher the surface is. According to the Rayleigh criterion [6], a surface is considered as smooth, if γ is less than 0.25, which results in the maximum path length difference of a half wavelength. When $\gamma = 0$, this scattering model degenerates to the specular reflection model. Let $\phi_{i,j}(t) = k\Delta l_{i,j}(t)$, which is the time varying phase of the complex amplitude associated to the $(i,j)^{th}$ path . The time varying amplitude $s_i(t)$ can be expressed as

$$\begin{aligned} s_i(t) &= \frac{s_i}{\sqrt{q_i}} \sum_{j=1}^{q_i} e^{j\phi_{i,j}(t)}, \\ &= \frac{s_i}{\sqrt{q_i}} \sum_{j=1}^{q_i} (\cos(\phi_{i,j}(t)) + j\sin(\phi_{i,j}(t)). \end{aligned} \quad (7)$$

When q_i is large, $\sum_{j=1}^{q_i} j\sin(\phi_{i,j}(t))$ approaches 0. Then,

$$s_i(t) \approx \frac{s_i}{\sqrt{q_i}} \sum_{j=1}^{q_i} \cos(\phi_{i,j}(t)). \quad (8)$$

Given γ, $\phi_{i,j}(t)$ is uniformly distributed in $[-2\gamma\pi, 2\gamma\pi]$. The expectation of $s_i(t)$ is

$$\mu_{s,i} = \mathbf{E}[s_i(t)] = \frac{s_i}{2\gamma\pi}\sin(2\gamma\pi), \quad (9)$$

which is nonzero in general. With multiple scattering clusters, the signal model is

$$\begin{aligned} h(t) &= \sum_{i=1}^{p} h_i(t) = \sum_{i=1}^{p} s_i(t) e^{jkl_{i,c}(t)}, \\ &= \sum_{i=1}^{p} s_i(t) e^{j\omega_i t}, \end{aligned} \quad (10)$$

where $\omega_i t = kl_{i,c}(t)$ is used in the last equation. In other words, the Doppler frequencies come into the signal via time varying path lengths.

An example of such a scenario with a single reflection cluster is given in Figure 1. The corresponding magnitude and phase of the time varying amplitude is given in Figure 2, where it can be seen that the amplitudes has approximately a linear phase, but time varying magnitudes. This observation coincides with those in [5].

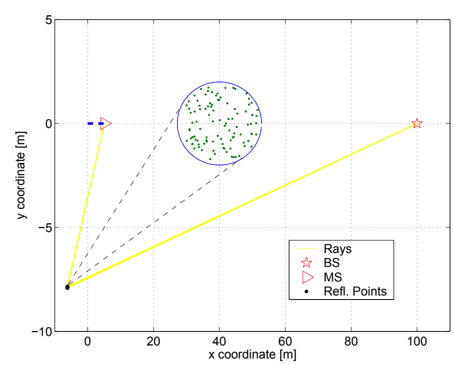

Fig. 1. Scattering on Rough Surface. (Single cluster $p = 1$, the number of reflection points $q_1 = 100$, the reflection points are uniformly distributed in a circular area with radius 0.25λ, the number of channel samples $N = 500$, the mobile velocity is $10m/s$, the distance from BS to the center of gravity of the scattering surface is 100 m, the distance from MS to the center of gravity of the scattering surface is 10 m, and the SNR is 10 dB.)

3. MODELING OF TIME VARYING AMPLITUDES

In (10), each time varying amplitude can be modeled as a low pass signal, since the time variations of the phases,$\Delta\phi_{i,j}(t)$,

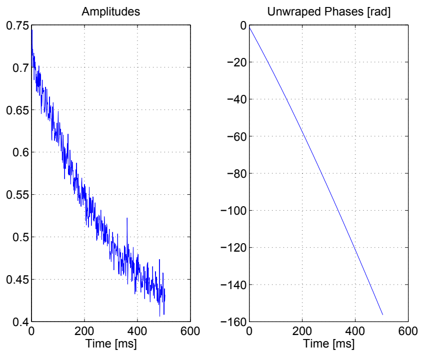

Fig. 2. Time Varying Amplitude due to Scattering Radiation on Rough Surface ($\gamma = 0.25$).

are functions of the mobile velocity, which is slow compared to the channel update rate (sampling rate). An AR(d) model is proposed to describe the dynamics of the amplitudes, where d is small. For the i^{th} cluster,

$$s_i(t+1) = \sum_{n=1}^{d} \alpha_{i,n} s_i(t-n+1) + v_i(t) = \boldsymbol{\alpha}_i^T \mathbf{s}_i(t) + v_i(t), \tag{11}$$

where $\boldsymbol{\alpha}_i = [\alpha_{i,1}, \cdots, \alpha_{i,d}]^T$, $\mathbf{s}_i(t) = [s_i(t), \cdots, s_i(t-d+1)]^T$. The $v_i(t)$ is a driving noise with pdf, $\mathcal{CN}(\mu_{v,i}, \sigma_{v,i}^2)$. Note that $\mu_{v,i} \neq 0$, and so is $\mu_{s,i}$.

One method to estimate those above mentioned parameters is proposed based the covariance sequences of $s_i(t)$, which is $r_{s,i}(K) = \mathbf{E}[s_i(t)\overline{s}_i(t-K)]$. The overline is conjugate operation. From (11), one can derive that

$$r_{s,i}(K) = \sum_{n=1}^{d} \alpha_{i,n} r_{s,i}(K-n) + \mu_{v,i}\overline{\mu}_{s,i}. \tag{12}$$

Given $r_{s,i}(K), K = 0, \cdots, M-1$, $\boldsymbol{\alpha}_i$ and $\mu_{v,i}\overline{\mu}_{s,i}$ can be estimated using LS, when $M > d+1$. Then the mean power of $v_i(t)$, $\|\mu_{v,i}\|^2$, can be estimated, since

$$\mu_{v,i}\overline{\mu}_{s,i} = \frac{\|\mu_{v,i}\|^2}{1 - \sum_{n=1}^{d} \overline{\alpha}_{i,n}}. \tag{13}$$

Since

$$r_{s,i}(0) = \boldsymbol{\alpha}_i^T \mathbf{R}_{s,i} \overline{\boldsymbol{\alpha}}_i + 2Re\{\boldsymbol{\alpha}_i^T \mathbf{1}_d \mu_{s,i}\overline{\mu}_{v,i}\} + \sigma_{v,i}^2 + \|\mu_{v,i}\|^2, \tag{14}$$

the variance of the innovation noise, $\sigma_{v,i}^2$, can be obtained, where

$$\mathbf{R}_{s,i} = \begin{bmatrix} r_{s,i}(0) & r_{s,i}(1) & \cdots & r_{s,i}(d-1) \\ r_{s,i}(-1) & r_{s,i}(0) & \cdots & r_{s,i}(d-2) \\ \vdots & \vdots & \ddots & \vdots \\ r_{s,i}(-d+1) & r_{s,i}(-d+2) & \cdots & r_{s,i}(0) \end{bmatrix}. \tag{15}$$

In a single scattering cluster scenario, $r_{s,1}(K)$ can be obtained easily from $\mathbf{y}$, since

$$r_y(K) = r_{s,1}(K) e^{j\omega_1 K} \quad \text{for } K \geq 1, \tag{16}$$

where $r_y(K) = \mathbf{E}[y(t)\overline{y}(t-K)]$. For $K = 0$, $r_y(0) = r_{s,1}(0) + \sigma_e^2$. With multiple scattering clusters, the estimation of covariance sequences of each cluster becomes tricky, since the sinusoidal signals with time varying amplitudes cannot be decoupled. However, it is still possible to estimate them, for example, by filtering in the frequency domain. More details about this will be presented in a future publication.

4. CHANNEL PREDICTION USING KALMAN FILTER

Define the zero-mean time varying amplitudes as $s_{z,i}(t) = s_i(t) - \mu_{s,i}$. The signal model (10) can be expressed in a state-space structure as

$$\mathbf{x}(t+1) = \boldsymbol{\Gamma}\mathbf{x}(t) + \mathbf{u}(t), \tag{17}$$

$$y(t) = \mathbf{c}(t)^T \mathbf{x}(t) + e(t), \tag{18}$$

where

$$\begin{aligned} \mathbf{x}(t) &= [\mathbf{x}_1(t)^T, \cdots, \mathbf{x}_p(t)^T]^T, \\ \mathbf{x}_i(t) &= [s_{z,i}(t), \cdots, s_{z,i}(t-d+1), \mu_{s,i}]^T, \\ \boldsymbol{\Gamma} &= diag(\boldsymbol{\Gamma}_1, \cdots, \boldsymbol{\Gamma}_p), \\ \boldsymbol{\Gamma}_i &= \begin{bmatrix} \alpha_{i,1} & \alpha_{i,2} & \cdots & \alpha_{i,d-1} & \alpha_{i,d} & 0 \\ 1 & 0 & \cdots & 0 & 0 & 0 \\ & & \vdots & & & \\ 0 & 0 & \cdots & 1 & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 1 \end{bmatrix}, \\ \mathbf{u}(t) &= [\mathbf{u}_1(t)^T, \cdots, \mathbf{u}_p(t)^T]^T, \\ \mathbf{u}_i(t) &= [v_i(t), \mathbf{0}_{d-1}^T, w_i(t)]^T, \\ \mathbf{c}(t) &= [\mathbf{c}_1(t)^T, \cdots, \mathbf{c}_p(t)^T]^T, \\ \mathbf{c}_i(t) &= [e^{j\omega_{c,i}t}, \mathbf{0}_{d-1}^T, e^{j\omega_{c,i}t}]^T. \end{aligned}$$

The variance of $w_i(t)$, $\sigma_{w,i}^2$, should be much smaller than the variance of $v_i(t)$, since $w_i(t)$ is the innovation noise for the mean amplitude which is constant. Then, the prediction of the $h(t+L)$ based on measurement $\mathbf{y}$ is

$$\hat{h}(t+L) = \mathbf{c}(t+L)^H \boldsymbol{\Gamma}^L \hat{\mathbf{x}}(t), \tag{19}$$

where $\hat{\mathbf{x}}(t)$ is obtained by the Kalman filter [7]. The initial covariance matrix $\mathbf{C}_\mathbf{x} = diag(\mathbf{C}_{\mathbf{x},1}, \cdots, \mathbf{C}_{\mathbf{x},p})$, $\mathbf{C}_{\mathbf{x},i} = diag([\sigma_{s,i}^2 \mathbf{1}_d^T, 0])$, and the initial state $\mathbf{x}(0|0) = \mathbf{0}$. The Doppler frequencies $\omega_{c,i}$ is estimated using ESPRIT [8]. The covariance matrix of $\mathbf{u}(t)$ is $\mathbf{Q} = diag(\mathbf{Q}_1, \cdots, \mathbf{Q}_p)$, $\mathbf{Q}_i = \mathbf{E}[\mathbf{u}_i(t)\mathbf{u}_i(t)^H] = diag([\sigma_{v,i}^2, \mathbf{0}_{d-1}^T, \sigma_{w,i}^2])$.

5. PERFORMANCE EVALUATION WITH A SINGLE CLUSTER

The proposed signal model (10) with single scattering cluster ($p = 1$) is adopted to evaluate the adaptive channel predictor in (19). To make the channel to be "easy" or "tough" to predict, γ is set to be 0.25 and 0.5 respectively. For each setting, 200 realizations are simulated. The averaged Normalized Square Error (NSE) over simulations is used to measure the prediction accuracy, where

$$NSE = \frac{N \cdot |h(t+L) - \hat{h}(t+L)|^2}{\mathbf{y}^H \mathbf{y}}, \tag{20}$$

which is termed Normalized Mean Square Error (NMSE). The LMMSE and the LP are also evaluated using the same data sets [4]. In the adaptive channel predictor, an AR(2) model is used. The orders of LMMSE and LP are 1. The results with $\gamma = 0.25$ and $\gamma = 0.5$ are presented in Figures 3 and 4 respectively. It can be seen that the adaptive channel predictor outperforms other methods in both cases. The LMMSE predictor based on constant amplitude has the worst performance. This results agree with those using measurement data. The performance of the adaptive channel predictor can be further improved by increasing the order of the AR modeling of the amplitudes or by using another model structure that better fits data.

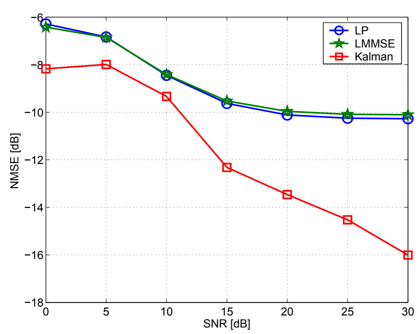

Fig. 3. Performance evaluation using simulated data. ($\gamma = 0.25$, prediction horizon L=5 (around 0.3λ))

6. CONCLUSIONS

Radio waves scattered on rough surfaces is modeled as sinusoidal signals with time varying amplitudes. This model is more realistic than the previously used sinusoidal modeling of a Rayleigh fading channel. An adaptive channel predictor using sinusoidal modeling with time varying amplitudes is proposed, where the time varying amplitude is modeled as an AR(d) process. The simulation results show that it outperforms all other methods in case of rougher surfaces. The LMMSE predictors based on constant amplitude has the worst performance among the tested methods.

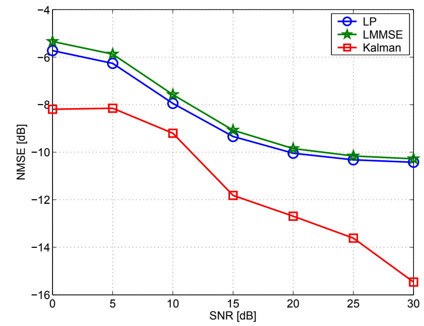

Fig. 4. Performance evaluation using simulated data. ($\gamma = 0.5$, prediction horizon L=5 (around 0.3λ))

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