A Novel Model of Time-Dispersion Multipath Channel for Wideband CDMA Systems

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ABSTRACT: We have suggested a novel time-dispersion multipath channel model for wideband wireless systems. This extended model incorporates the microcell site-specific information by including the frequency dependence of individual paths. A new super-resolution algorithm has been used to estimate the path delay and frequency dependence of each individual path.

INTRODUCTION

The time-varying wideband dispersive wireless channel model is the bread and butter for the study of the wireless systems [1]. A lot of wireless communications branches such as modulation, detection, error coding, multi-user receiver, antenna, and radio link design depend heavily on the results of such propagation channel models. This is the case, especially at this time some types of wireless environments for in-building propagation, microcellular propagation, and PCS are not well understood. The so-called smart (adaptive) antenna system or spatial filtering speeds up the necessity of the understanding of individual multipath signal. The smart antenna is another key technique to improve the capacity of the CDMA systems [2]. On the other hand, especially in environments where multipath is a limiting factor, in the reverse link the use of smart antenna at the base station enhances the performance of the CDMA system.

The objective of this paper is to study a novel wideband wireless multipath channel with path frequency dependence [3-5]. We already understand that the incorporation of path frequency dependency provides insights into the individual multipath signals, although such frequency dependence produces a relatively small impact on the channel frequency response function. However, in a lot of wireless scenarios, not just the channel frequency response function matters. The time information of individual multipath signals, such as the angle-of-arrival (AOA) for smart antennas, the path delay for RAKE receiver and diversity, is very important to wideband wireless systems, particularly CDMA systems. This motivates the deeper study of multipath signals [3]. Instead of emphasizing the physics of path frequency dependence [5], we here focus on identifying the individual multipath signals and the corresponding signal processing algorithm. An relatively novel algorithm has been developed [3-4]. In this contribution, the focus is on the microcellular environment with DS-CDMA and spatial filtering in mind.

A Novel Multipath Channel Model

Mathematically, the impulse response of the modified multipath fading channel in the frequency domain is given by [3-5]

$$H(\omega) = \sum_{k=1}^{N} \beta_k e^{j\phi_k} \frac{\alpha_k}{\omega} e^{-j\omega \tau_k}$$

where $N$ versions of the transmitted signal are assumed to be received. Frequency dependencies $\omega^\alpha$ of common structures have been listed in Table 1. For instance, for a single wall edge diffraction, we have $\alpha$=-0.5 or $1/\omega^{0.5}$. For a double wall edge diffraction, we have $\alpha$=-1 or $1/\omega$. We should mention three points. First, the signal transmitted from the base station reaches the portable radio receivers via one or more main waves. Second, these main waves may consist of a line-of-sight ray and several rays reflected and/or diffracted by main structures like outer walls, floor, ceiling, furniture, etc. Third, the main paths may arrive with too close delays to resolve, but have different frequency dependence. In this situation, we can detect the “effective frequency dependence” of the merged observable.

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1 This work was performed while the first author was with Polytechnic University.
Table 1 Physical Mechanism versus Frequency Dependence

<table>
<thead>
<tr>
<th>Physical Mechanism</th>
<th>Frequency Dependence Factor $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diffraction from smooth or flat surface</td>
<td>0</td>
</tr>
<tr>
<td>Diffraction by Edge</td>
<td>-0.5</td>
</tr>
<tr>
<td>Diffraction by Corner or tip</td>
<td>-1</td>
</tr>
<tr>
<td>Diffraction by Axial Cylinder Face</td>
<td>+0.5</td>
</tr>
<tr>
<td>Diffraction by Broadside of a Cylinder</td>
<td>+1</td>
</tr>
</tbody>
</table>

Channel Estimation by a Novel Algorithm

We sample our signals in (1) using $\omega = \omega_0 + n \cdot \omega_s$; $n=0,1,2,...,N$, where $\omega_0$ is the lowest angular frequency, $\omega_s$ is the sampling interval in the frequency domain, $m$ is the sample index, and $N=2N_0+1$ is the total number of samples in the frequency domain. Using a Taylor series, we get

$$H[n] = H(\omega_0 + n \cdot \omega_s) = \sum_{k=1}^{N} a_k Z_k^n$$

$$Z_k = \exp(i \frac{ \alpha_k + j \cdot \tau_k \cdot \omega_s }{ \omega_0 }) \quad a_k = \beta_k e^{i \phi_k \omega_0}$$

The next step is to use a high resolution algorithm to estimate the complex amplitudes and complex exponentials given in (2)-(3). This step is the most critical in the whole process. For practical applications, there are three important criteria: (1) no spurious poles; (2) accurate; (3) robust. The first criterion says the algorithm gives only true poles. This is very important for practical applications. To our best knowledge, it seems that only the Eigen-Matrix Pencil Method described below has this feature. In addition, this method is also accurate and robust in case of white Gaussian noise. For detail, see also [4].

We describe the seven basic steps of our algorithm as the following:

Step 1 Form the Hankel matrix $H$ using the measured noisy complex data sequence $x[n]$, $n=0,1,...,N-1$, where $N=2N_0+1$.

$$H = \begin{bmatrix}
\vdots & \vdots & \vdots & \ddots & \vdots \\
x[N_0] & x[N_0+1] & x[N_0+2] & \ldots & x[2N_0] 
\end{bmatrix}$$

Step 2 Keep only the $M$ principal components and rebuild the matrix $H_0$ using only the $M$ singular values and their associated eigenvectors. The number of signals $M$ is known a priori, or estimated by some approaches such as the SVD expansion of the matrix $H$. We have

$$H = \sum_{m=1}^{N} \sigma_m u_m v_m^H$$

and

$$H_0 = \sum_{m=1}^{M} \sigma_m u_m v_m^H$$

where $\sigma_m$ is the $m$-th singular value of matrix $H$. $u_m$ and $v_m$ are, respectively, its associated left and right singular vectors of matrix $H$. The matrix $H_0$ is a rank-$M$ approximation of matrix $H$. This is a de-noise process that improve the effective SNR of the processed data.

Step 3 Find the complex eigenvalues $\gamma_n$ and associated eigenvectors $e_n$ of the matrix $H_0$, such that

$$H_0 e_n = \gamma_n e_n \quad n=1,2,...,N_0+1$$

Step 4 Form the $N_0 \times M$ eigen-matrix $E_1 = [e_1, e_2, ..., e_M]$. Then form the $L \times M$ eigen-matrix $F_1$ using the first $L$ rows of $E_1$ ranging from the first row to the $L$-th row of $E_1$, and another $L \times M$ eigen-matrix $F_2$ using the next $L$ rows of $E_1$, ranging from the second row to the $(L+1)$-th row of $E_1$.

Step 5 Form the eigen-matrix pencil $\{F_1^H F_1, F_1^H F_2\}$ and find its complex generalized eigenvalues $\lambda_m$, $m=1,2,...,M$. The generalized eigenvalues are defined as the roots of the following equation

$$p(\lambda) = \text{det}(F_1^H F_2 - \lambda F_1^H F_1) = \text{det}(F_1^H Z_k) \cdot \text{det}(I_M - \lambda D) \cdot \text{det}(D) = 0$$

where "det" denotes the determinant of the matrix. In (8), we have use the relation

$$(F_1^H F_1) - \lambda (F_1^H F_2) = (F_1^H Z_k)(I_M - \lambda D)$$

In (8)-(9), $Z_k$ is a matrix with a full rank $M$. $D$ of $M \times M$ is square with rank $M$, and thus is nontrivial. $I_M$ is a $M$-dimensional identity matrix. $\Delta$ is an $M \times M$ diagonal matrix with the $m$-th element defined by (2) and (3).

Step 6 Obtain the $M$ signal poles using

$$z_m = \lambda_m^{-1} \exp(i \frac{ \alpha_m + j \cdot \tau_m \cdot \omega_s }{ \omega_0 })$$
m=1,2,...,M, where \( \alpha_m \) is the frequency dependency factor of the m-th path.

Step 7 Obtain the residues \( a_k = \beta_k e^{i\theta_k} \omega_0^{\alpha_k} \), \( k=1,2,...,M \) using the least square fitting of the \( N=2N_0+1 \) data. This step is similar to the standard Prony method.

For details regarding those 7 steps, we refer to [3].

**Results**

CDMA systems tend to be self-interferenced limited. In other words, when multiple users share the RF channel simultaneously, the mutual interference (multiple access interference), not the thermal noise, sets a limit on the number of the simultaneous active users. It is a difficult issue to accurately model the mutual interference. Fortunately, the probability distribution of the interfering signals is often approximated as Gaussian. This is reasonable since the interfering signal sequence contributions are the sum of a large number of binomial random variables, which closely approximate Gaussian random variables (central limit theorem). The cochannel interference effects and channel noise are simulated by adding the additive Gaussian noise. In practical systems, the background noise due to interference and environmental excess noise could be very high. It is interesting to study the algorithm under different signal-to-noise ratios (SNRs). On the other hand, the resolution of the algorithm is determined by the measurement bandwidth. If the sampling period is kept fixed, the bandwidth is given by the length of the total samples \( N \).

In Fig. 1 (a)-(c), we have estimated two damped exponentials using the SVD Prony method and the Pencil method [6], and the SVD Eigen-Matrix Pencil method. Parameters: \( N=25 \), \( \text{SNR}=15 \text{ dB} \). Our algorithm has got best performance. The SVD Prony method has spurious poles. This is one of the most difficult problems in estimating the channel parameters. Although the pencil matrix method by [6] avoids this spurious pole problem, it produces the wrong poles in case of noise.

Fig. 2 (a)-(c) gives the performance of our new algorithm with short measurement bandwidth or short length of data samples. Our algorithm can work for very short data samples under reasonable SNRs.

In Fig. 3, we have estimated the time delays and frequency dependency factors of the wideband channel using the newly developed algorithm. We have made 500 Morte Carlo runs, and the means of those runs are shown in Fig. 3. This algorithm can work at very low SNR up to 10 dB for time delay estimation.

To characterize our algorithm statistically, in Fig. 4 we have compared the estimation variance values of our algorithm with the benchmark—the Cramer-Rao bound, which gives the theoretical limit an algorithm can possibly achieve. Our algorithm goes close to the Cramer-Rao bounds. This means that our algorithm is almost optimal.
corner diffraction or two edge diffractions, and the ray with \( \alpha = -1.5 \) in the fourth row undergoing one corner and one edge diffraction or three edge diffractions. Other rays are more likely just experiencing some reflections, since there is no frequency dependence. The combination of the time delay, amplitude and the frequency dependence as well as the geometric

Fig. 2 Estimation of damped exponentials using the SVD Eigen-Matrix Pencil Method. (a) \( N=15, \text{SNR}=20 \) dB, (b) \( N=15, \text{SNR}=15 \) dB, (c) \( N=11, \text{SNR}=20 \) dB

In addition to providing the super-resolution of the power profile of a channel, our approach can also supply the path delay and frequency dependence of an individual path, which are given in Table 2. The frequency dependence has been accurately estimated. From the estimated values in Table 2, the frequency dependence provides information about the "path history" of these rays. For example, from \( \alpha = -0.5 \), we know the ray with the arrival time delay of 80(ns) in the first row experiencing an edge diffraction by a wall, the ray with \( \alpha = -1 \) in the seventh row encountering a

Fig. 3 Estimation of channel parameters through SVD Eigen-Matrix Pencil Method. (a)-(b): without SVD; (c)-(d): with SVD.

Fig. 4 The Cramer-Rao Lower Bounds versus the variance values estimated through 500 Monte Carlo runs. Solid: Cramer-Rao bounds; Dotted and Daggered: our algorithm

layout of the physical channel can provide us more physical insights into the indoor or outdoor propagation channel. Based on such a combination, a tool can be devised to detect the ray propagation path. This might be relevant to the receiver design, a tool can be designed to detect the ray propagation path. Then an approach that reduces the path delay and frequency dependence to the complex poles of the measured or
simulated signal consisting of only complex exponentials has been adopted. Further, a new super-resolution algorithm called the SVD Eigen-Matrix Pencil Method has been used to estimate the complex poles, and then the path delay and frequency dependence. To characterize the performance of our approach to estimate the channel parameters from the measured or simulated data, a number of numerical results through the simulation of the two-path channel and the 8-path channel are given. We choose typical values of the bandwidth and the frequency band for measurement use.

TABLE 2 Estimation of Time Delays and Frequency Dependencies of a Simulated Wireless Microcell Propagation Channel Using a Novel High-Resolution Algorithm

(Channel Parameters: Lowest Frequency $f_0=900$ MHz, Frequency Sample Spacing $f_s=1.875$ MHz; Total Samples N=100)

<table>
<thead>
<tr>
<th>True Path Delays (ns)</th>
<th>Estimated Path Delays(ns)</th>
<th>True Frequency Dependence</th>
<th>Estimated Frequency Dependence</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td>80.0000</td>
<td>-0.5</td>
<td>-0.50</td>
</tr>
<tr>
<td>100</td>
<td>101.3333</td>
<td>0</td>
<td>0.0001</td>
</tr>
<tr>
<td>120</td>
<td>117.3333</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>140</td>
<td>141.3336</td>
<td>-1.5</td>
<td>-1.58</td>
</tr>
<tr>
<td>160</td>
<td>166.3333</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>180</td>
<td>184.000</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>200</td>
<td>200.000</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>220</td>
<td>226.686</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Conclusion

A new algorithm has been developed and characterized. This algorithm is almost optimal in the sense of Cramer-Rao bounds. This algorithm has been used to identify the channel parameters such as time delay and frequency dependency of an individual path. The amplitude of a path can be obtained simultaneously as well. The frequency dependency can be used to trace, detect, and characterize a ray path. After tracing the frequency dependence of individual ray paths, we can gain more insights into the propagation features of a specific indoor and outdoor channel. These insights should find important applications in channel modeling, especially site-specific channel modeling. The frequency dependence is important to system performance, and the extended channel model might facilitate measurement campaigns as well. Finally we believe that the work reported here should be able to find applications in wireless communications such as channel modeling, RAKE receiver, cochannel interference, power control, multiple access and diversity techniques.

Reference