Modeling Fading Properties for Mobile Satellite Link Channels Using Markov Model Approaches

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Abstract — In this paper, the fading properties of satellite-to-earth propagation channels are predicted using different Markov models. The proposed methods are validated and evaluated using mobile satellite link measurements data at typical mobile user environments. Compared with multi-states Markov models and traditional hidden Markov model, a better match between simulated and measured data shows that the non-stationary hidden Markov model predicts most satisfactorily the first and second order statistics of propagation properties. Besides, the proposed Markov models can be applied to evaluate the performance of error probability using coherent QPSK modulation schemes. This simple and efficient method extends the applicability of the Markov model approach in propagation channel modeling for satellite mobile communication services.

1. Introduction

To predict the actual service performance for both land mobile satellite systems (LMSSs) and satellite personal communication services (S-PCSs), channel simulation and modeling are necessary. All S-PCSs, whether targeted for vehicular or personal use and whether operating at UHF, L-, S-band or higher frequencies, are ultimately performance limited by propagation fading properties. The line-of-sight signals may be clear, shadowed by trees or blocked by solid objects, i.e. buildings and mountains. It is shown that the switching between different attenuation levels can be represented as a Markov stochastic process using the assumption that the channel properties are quasi-stationary over small period time \([1, 2]\). Propagation channels can be considered as operating in one of a finite number of possible channel states. A Markov chain is a stochastic process with a set of states. At any given time, the process starts in one of these states and move successively from one state to another. The probability of moving a state to another does not depend upon which states the chain was in before the current state. Although the fading properties can be predicted, but those are hard to obtain correctly curve fit using pure Markov chain model (such as multiple states Markov model). This limitation was due to the relationship consideration between two adjacent states of a pure Markov chain model. We therefore propose new methods based on hidden Markov models (HMMs) to predict satellite propagation fading \([3, 4]\). The HMM can simultaneously model a fading channel with memory (signals field time vary) and relationship between two adjacent states. In this paper we evaluate the three kinds of Markov channel models: the multiple states Markov model, traditional hidden Markov model and non-stationary hidden Markov model. We briefly discuss each of the three kinds of Markov models and their parameters. The proposed methods are validated and evaluated using mobile satellite link measurements data at typical mobile user environments. Besides, In order to illustrate the performance evaluation of the modulation technique, quadrature phase shift keying (QPSK) is chosen as an example.
2. Discussion of The Three Models

The Markov chain method is widely applied to model propagation channel properties [1, 2]. However, the HMM is more excellent for channel modeling because of its memory characteristics [5]. Beside, we further improve the state occupation duration problem by introducing non-stationary HMM [6]. The briefly discuss on the three Marko models and their parameters is in the follows:

A. Multi-States Markov Model

In previous work [1], environmental images were processed to derive Markov matrices and state transition matrices, and conventional three-state propagation channel simulation algorithm was used to obtain a statistical representation of the communication channel. However, images take times and memory spaces for processing. For more accuracy and easier prediction, increasing the number of states and adopting less complicated propagation channel model are necessary. In wireless communication, the propagation channel can be characterized as slow fading and fast fading channel. The model assumes that the signal variation due to attenuation of line-of-sight is slow fading (lognormal) and that the variation due to multipath is fast fading (Rayleigh). Utilizing two Markov transition matrices (contain slow and fast fading matrices) can introduce more states for achieving higher accuracy with easier processing. The multi-state Markov model describes a typical propagation link as a sequence of finite number states and propagation channels can be considered as operating in one of the possible state. The switching between different attenuation levels can be represented as Markov stochastic process using the assumption that the channel properties are quasi-stationary in small time periods. In the simulation procedure, the received signal is divided into small frames and each frame is represented by a state. Each single state is represented by Loo’s distribution function with a corresponding set of parameters. The detail description of this method and the modeling procedures can be found in [3].

B. Hidden Markov Model

The parameters of HMM can be defined as $\lambda=\{\pi, A, B\}$, $\pi$ are the state initial probabilities, $A$ is the state transition probability, and $B=\{b_j(x)\}$ is the output conditional probability density in state $j$, the general form of $b_j(x)$ for a continue HMM is

$$b_j(x) = \sum_{m=1}^{M} c_{jm} f(x, \mu_{jm}, \Omega_{jm}) 1 \leq j \leq N$$

where $N$ is the number of states, $x$ is the observation condition being modeled, $c_{jm}$ is the mixture coefficient for the $m$th mixture in state $j$ and $f(\cdot)$ is any log-concave or elliptically symmetric density, with mean $\mu_{jm}$ and covariance $\Omega_{jm}$ for the $m$th mixture component in state $j$. In our case, to simplify the probability calculation and re-estimation problems, we set $M=1$ and $f$ be a Gaussian density [5] to have

$$b_j(x) = \frac{1}{\sqrt{2\pi\Omega_j}} e^{-\frac{1}{2}(x-\mu_j)^T\Omega_j^{-1}(x-\mu_j)} 1 \leq j \leq N$$

And the matrix $A$ is assumed a birth-death process. We can improve the algorithm efficiency of the Baum-Welch algorithm to reduce the number of calculation multiplication. The detail discussion on model parameters and modeling procedures about this method can be found in [4].
C. Non-stationary Markov Model

Hidden Markov models are widely used for modeling random processes. Drawbacks in a standard hidden Markov model for modeling state occupancy have often been pointed out. This limitation motivates us to study a more general form to overcome this essential problem and a modified model has been presented. Consider a tradition hidden Markov chain process with \( N \) states, it is obvious that the state duration density probability function is a geometric distribution, if the state transition matrix \( A \) is a \( N \times N \) matrix. For most applications, this geometric state duration distribution is inappropriate for modeling real-world signals. Our proposed model explores the state transition matrix to form two to three dimensions, i.e. translating \( \{a_{ij}\} \) into \( \{a_{ij}(d)\} \), where \( 1 \leq i, j \leq N \), \( 1 \leq d \leq D \). From the nonstationary hidden Markov model definition [6], it can be observed that the state transition probability is a function of the time spent in the previous state. The state transition probability can be written as :

\[
 a_{ij}(\tau) = P(q_i = j | q_{i-1} = S_i, q_{i-2} = S_{i-1}, \ldots, q_{i-\tau} = S_{i-\tau})
\]

(3)

Based on this assumption, we will further generalize it to continue the output vision and get the parameters of re-estimation formula to solve the state occupancy problem.

3. Model Validations

The proposed Markov models are applied to validate the model accuracy by using real satellite fade data measurement at typical user environments: rural, wooded, and suburban. The measurement data were obtained by recording 2055 MHz CW transmissions from a TDRS geostationary satellite at 21° elevation and 249° azimuth. The cumulative distribution (CDF) of fade time series, level crossing rate (LCR), and error probability performance using QPSK modulation scheme were calculated to characterize the propagation properties and service performance of satellite propagation paths at three different typical mobile user environments. The rms errors between the measured and simulated data for three kinds of Markov model are listed in Table 1. Compared with multi-states Markov models and traditional hidden Markov model, as shown in Fig. 1, a better match between simulated and measured data shows that the non-stationary hidden Markov model predicts most satisfactorily the first and second order statistics of propagation properties.

4. Conclusions

In this paper, the fading properties of satellite-to-earth propagation channels are predicted using different Markov models. The proposed methods are validated and evaluated using mobile satellite link measurements data at typical mobile user environments. The results show that the non-stationary HMM method has best performance in modeling fading properties of satellite propagation channels. We also show the promise of using non-stationary HMM method for predicting the service performance of the satellite communication systems.

Acknowledgments
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References


Table 1 The rms errors of the C.D.F., B.E.R., and L.C.R. between simulated and measured signals by using Multi-state, HMM, and Non-stationary HMM methods.

<table>
<thead>
<tr>
<th></th>
<th>CDF</th>
<th>BER</th>
<th>LCR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MSMM</td>
<td>HMM</td>
<td>NSHMM</td>
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<tr>
<td>Rural</td>
<td>0.0085</td>
<td>0.0072</td>
<td>0.0040</td>
</tr>
<tr>
<td>Wooded</td>
<td>0.0160</td>
<td>0.0226</td>
<td>0.0055</td>
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<tr>
<td>Suburban</td>
<td>0.0070</td>
<td>0.0022</td>
<td>0.0010</td>
</tr>
</tbody>
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Figure 2. The statistical properties comparison between simulated results and measured results in time series (left), C.D.F. (upper right), L.C.R. (center right), and B.E.R. (lower right) for wooded case. [solid line: measured, dash line: Non-stationary HMM, dot line: HMM, dash-dot line: Multi-state MM]