Research Article

An Alternating Variable Step-Size Adaptive Long-Range Prediction of LMS Fading Signals

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Received 9 October 2014; Revised 26 January 2015; Accepted 6 February 2015

Academic Editor: Li Zhuo

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We propose a linear alternating variable step-size adaptive long-range prediction (AVSS-ALRP) scheme to predict fading signals which is especially suitable for a versatile two-state land mobile satellite (LMS) channel model at S-band. A three-step design procedure is presented to optimize the prediction performance. Firstly, we establish the Gilbert-Elliot channel model based on first-order Markov chain for satellite communication downlink and take advantage of smoothing average to obtain channel observed values. At a second stage, eigenvalue decomposition method is applied to predict future long-range channel state instead of weighted prediction. Finally, combining variable step-size least mean squares and adaptive long-range prediction, we introduce the VSS-ALRP algorithm to predict LMS channel fading signals in the case of “good” state, and the obtained prediction results would be revised based on the linear prediction of error when shadowing condition is in the “bad” state. Simulation results show that the proposed scheme cannot only offer an accurate prediction for long-range channel state and fading signals over the two-state Gilbert-Elliot channel model and greatly enhance the fading signals’ autocorrelation, but also have considerably better performance than long-range prediction (LRP) algorithm from the results of mean square error (MSE) and correlation coefficient.

1. Introduction

As an important part of land mobile satellite (LMS) communication systems, the LMS channel will affect the reliability of transmitted signal distorted by multipath, shadowing, or obstacles between satellite and receiver when mobile terminal is in the situation of fast movement. In order to achieve a good trade-off between power efficiency and spectral efficiency for LMS communication systems, domestic and foreign scholars take advantage of the accurate channel information which is fed back to the transmitter to adjust the parameters of adaptive coded modulation and multiple-input multiple-output (MIMO) [1–3]. However, the predicted information would be inaccurate and rapidly outdated due to the abrupt change of shadowing state, blocked behavior, and large propagation delay of LMS channel in the case of fast movement. To ensure the reliable adaptive transmission for LMS communication systems, the fading signals need to be accurately predicted in advance. The main work in this paper is to study the long-range prediction of LMS fading signals including two aspects; that is, one is to model a flexible LMS channel at S-band and make it effective in the different shadowing conditions and the other is to provide a reliable prediction scheme for the fading channel.

The existing algorithms are practical and effective for short delay prediction of terrestrial wireless mobile fading channel, such as long-range prediction (LRP) with least mean square filter [4, 5], adaptive long-range prediction (ALRP) [6], and Kalman filter [7]. Nevertheless, the drawbacks of such algorithms applied to LMS fading signals are as follows: the sum of sinusoid model is established based on the physical scattering mechanism, and the prediction performance decreases quickly when the future long-range prediction is much longer than the correlation time of observed values.

In recent years, a survey of the state-of-the-art modeling methods concerning the LMS channel is provided in [8]. The long-range fading signals are difficult to be predicted for LMS channel when the channel is in the condition of larger propagation delay and variable shadowing with travelled distance. A linear prediction based FIR channel estimator is proposed based on Loo channel model [9]. Zhou and Cao analyzed
the predictability of LMS channel and presented a linear long-range prediction algorithm by combining the weighted prediction and LRP algorithm [10]. The nonlinear autoregressive integrate moving average (ARIMA) and smooth-ARIMA prediction algorithms were proposed based on LTE-compatible low earth orbit (LEO) and geosynchronous orbit (GEO) mobile satellite communication systems [11, 12]. An ALRP of fading signals over three-state LMS channel was presented by [13]. The above-mentioned prediction schemes are inflexible and complex caused by fixed propagation parameters in channel model and transition among three states as well as multistep prediction. Meanwhile, the prediction performance is degraded because of a relative low correlation, error propagation, autoregression (AR) model stationary parameters, and fixed step-size. Up to now, the practical prediction scheme for solving the above problem has not been discussed yet. In this paper, a linear alternating prediction scheme is considered instead.

Aiming at the above-mentioned problems, we directly obtain the observed values of fading signals through a versatile two-state LMS channel model which has the outstanding advantage in flexibility about selection of propagation parameters and universality application for more scenarios and then introduce smoothing average method to prevent the received signals’ correlation from decreasing. In addition, a novel linear alternating variable step-size adaptive long-range prediction (AVSS-ALRP) algorithm inspired by [14] is proposed by combining with eigenvalue decomposition [15] to improve prediction performance.

The rest of the paper is organized as follows. Section 2 introduces the structure of two-state Gilbert-Elliot channel model with variable propagation parameters briefly. Section 3 expounds the proposed scheme in detail including the eigenvalue decomposition prediction, variable step-size adaptive long-range prediction (VSS-ALRP) algorithm, error prediction, and computational complexity analysis. Simulations are discussed in Section 4. Finally, we conclude the paper in Section 5.

2. Two-State Gilbert-Elliot Channel Model

To reduce the complexity of state transitions and increase the randomness of channel fading signals compared with other models in the literature [16–19], we use a two-state Gilbert-Elliot channel model to characterize the changes of shadowing conditions with travelled distance for the LMS channel. The shadowing conditions are divided into “good” and “bad” states that represent a range of LoS-to-moderate shadowing and deep-to-blocked shadowing, respectively, according to the fading of line-of-sight (LoS) [20]. The implementation block diagram of fading signals is illustrated in Figure 1, which consists of state sequence generator (SSG), propagation parameter generator (PPG), and small-scale fading generator (SSFG).

The complex fading signals are composed by multipath and shadowing fading within each state as shown in Figure 1. The probability density function of the envelope is denoted
as a stationary Loo distribution [21]. Each time a new state is reached, a Loo parameter triplet is updated by the joint probability distribution, which can be expressed as

\[
\begin{align*}
    f(M_A) &\sim N(\mu_1, \sigma_1), \\
    f(\Sigma_A | M_A) &\sim N(\mu_2, \sigma_2), \\
    f(MP) &\sim N(\mu_3, \sigma_3),
\end{align*}
\]

(1)

where

\[
\begin{align*}
    \mu_2 &= a_1 \times M_A^2 + a_2 \times M_A + a_3, \\
    \sigma_2 &= b_1 \times M_A^2 + b_2 \times M_A + b_3,
\end{align*}
\]

(2)

where MP, \(M_A\), and \(\Sigma_A\) are multipath average power and the mean and standard deviation of log-normal distribution, respectively, which are all given in dB. The coefficients \(a_i\), \(\sigma_1\), \(a_i\), and \(b_i\) are fixed for a given environment type, satellite elevation, and azimuth. For 60° elevation and mobile speed of 12.5 m/s in intermediate tree-shadowed environment at S-band, the simulated fading signals are shown in Figure 2. With regard to the travelled distance scales, we can clearly observe that the channel model describes two different shadowing states and the large dynamic range of fading signals envelope due to variable propagation parameters. The excellent reliability of the model has also been verified by [20], and the model has been widely used in many practical systems, for example, digital video broadcasting via satellite handheld (DVB-SH) system, mobile satellite channel for angle diversity (MiLADY) system [22, 23], MIMO system [24], and so forth.

3. ALRP of LMS Fading Channel

Because of long transmission delay (about 266.66 microseconds) at S-band and time-varying shadowing conditions as well as the abrupt deep shadowing state, LMS communication systems will result in the performance degradation of channel prediction. For the sake of achieving a more accurate prediction performance, we firstly predict channel shadowing state by using eigenvalue decomposition method and then adopt the smoothing average to obtain the observed values of fading signals. Finally, the future fading signals are predicted based on linear VSS-ALRP algorithm if the current shadowing condition is in the case of “good” state; otherwise the predicted results will be modified by combining with linear prediction of error within “bad” state.

3.1. Prediction of Future Channel Shadowing State. The eigenvalue decomposition method rather than weighted prediction is chosen to improve the prediction accuracy of channel shadowing state for avoiding the twice sampling of channel observed values and reducing state prediction error. According to state frame or minimum state length of 3~5 m at S-band indicated by [16], Figure 3 shows the state transitions model governed by a first-order discrete-time Markov chain.

In Figure 3, \(p_{211} = p_g\) is the transition probability from “good” to “bad” state and \(p_{12} = p_b\) is the transition probability from “bad” to “good” state. \(b_i, i = 1, 2\), represent the observed values of fading signals directly obtained through the two-state LMS channel model within state \(i\). So the state transition probabilities’ matrix is given by

\[
P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} = \begin{bmatrix} 1 - p_g & p_g \\ p_b & 1 - p_b \end{bmatrix}. \tag{3}
\]

The eigenvalues of (3) are \(\lambda_1 = 1\) and \(\lambda_2 = 1 - p_g - p_b\), and the corresponding eigenvectors are \(S_1 = [1 \ 1]^T\) and \(S_2 = [p_g \ -p_b]^T\), respectively. Therefore, \(P\) can also be conveniently denoted as matrix form

\[
P = SAS^{-1}, \tag{4}
\]

where

\[
S = \begin{bmatrix} 1 & p_g \\ 1 & -p_b \end{bmatrix}, \quad \Lambda = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \tag{5}
\]
are the eigenvector and eigenvalue matrices, respectively. \( P_G \)
and \( P_g \) are the probabilities of the “good” and “bad” states and
are defined as
\[
P_G = \frac{P_b}{P_b + P_g}; \quad P_g = \frac{P_g}{P_b + P_g}.
\]  (6)

Through (3), (4), and (6), the transition probabilities
matrix \( P^m \) of the \( m \)th state frame is derived by
\[
P^m = SA^mS^{-1}
= \frac{1}{P_b + P_g} \left[ \begin{array}{cc}
P_b(1 - \lambda_2^m) & P_g(1 - \lambda_2^m) \\
\lambda_2^m P_b & \lambda_2^m P_g
\end{array} \right]
\]  (7)

The prediction error of channel shadowing state in the
\( m \)th state frame when the initial state is “good” or “bad” can be
expressed as
\[
F_g (m) = 2 \times \left( p_b + p_g \lambda_2^m \right) \times \frac{p_g (1 - \lambda_2^m)}{p_b + p_g}
= 2 \times \left[ P_G (1 - \lambda_2^m) + \lambda_2^m \right] p_B (1 - \lambda_2^m),
\]  (8)
\[
F_b (m) = 2 \times p_b (1 - \lambda_2^m) \times \frac{p_b + p_g \lambda_2^m}{p_b + p_g}
= 2 \times P_G (1 - \lambda_2^m) \left[ p_B (1 - \lambda_2^m) + \lambda_2^m \right]
\]

The prediction error can be derived from the state
transition probabilities; that is,
\[
F_e = F_g p_b + F_b p_g = 2 \times (1 - \lambda_2^m) p_g p_b.
\]  (9)

It is observed that \( F_e \) is approaching the maximum value
when both \( p_b \) and \( p_g \) are close to 0.5, and a large \( m \) will
cause a fast convergence. The prediction error is below or
equal to 10% as long as any one transition probability is
less than 0.05. That is to say, the prediction performance is
improved when the shadowing condition with low transition
probability remains unchanged for a long time.

3.2. Alternating Variable Step-Size Adaptive Long-Range
Prediction Algorithm. The LMS channel has the nature of long
transmission delay and fast time-varying fading compared
with the terrestrial wireless mobile channel, which will cause
a decrease in prediction performance. So a desired ALRP
algorithm for LMS channel is necessary to compensate the
outdated problem and improve the prediction performance.
There are two main problems to be solved in the process of
applying ALRP algorithm into two-state LMS channel—high
prediction error during “bad” state duration and AR model
instability parameters. They can be solved to some extent
by updating the step-size parameter according to correlation of the
latest observed values in the tracking model and
predicting the error of ALRP algorithm. Based on the above-
mentioned fact, a novel linear AVSS-ALRP algorithm, which
uses a variable step-size parameter in the update equation,
is proposed. In this algorithm, the channel fading signals are
predicted by applying VSS-ALRP in the case of “good” state,
and the obtained prediction results would be revised based
on the linear prediction of error if shadowing condition is in
the “bad” state.

We consider 1-step linear prediction of the future channel
fading signals. The prediction of \( b_n \) using the latest \( K \) previous
observed values based on linear AR model can be expressed by
\[
\hat{b}_{n+1} = a_0 b_{n-1-j} + \cdots + a_{K-1} b_{n-K} + \delta_{qi}
\]  (10)

where \( \delta_{qi} \) is the difference of the mean of channel fading
signals between state \( q \) and state \( i \). \( d = [d_0, \ldots, d_{K-1}]^T \)
are the optimal initial coefficients of the AR model within a predicted
state \( i \) estimated by solving the Yule-Walker equations [25]
firstly.

The reduced correlation of channel fading signals over
time, the assumption of fixed coefficients throughout the state
duration, and the error propagation caused by previously
predicted values make the prediction performance decrease.
So, the initial coefficients of state \( i \) are estimated by using the
minimum mean square error approach in the nontracking
mode, and the coefficients are updated by using the variable
step-size adaptive iterative method [26] in the tracking mode.
Let us consider \( q_n \) as a smooth parameter at time \( n \) given by
\[
q_n = \beta q_{n-1} + (1 - \beta) \sum_{j=0}^{K-1} \left[ b_{n-1-j}^e b_{n-1-j}^e \right]^2.
\]  (11)

At time \( n + 1 \), the step-size based on positive parameters
\( \alpha, \beta, \) and \( \gamma \) is shown as follows:
\[
\mu_{n+1} = \alpha q_n + \gamma q_n
\]  (12)

Subsequently, the update equation of coefficients can be
determined using \( K \) previous observed values to follow the
channel fading variations as
\[
d_{n+1} = d_n + \mu_{n+1} e_n b_n^H
\]  (13)

where \( e_n = \hat{b}_n - b_n \) is the channel prediction error.

The LMS channel is nonstationary during a short period
after the appearance or disappearance of “bad” state. The
proposed VSS-ALRP algorithm could take a relative long
convergence time which will result in a bad performance due
to a big step-size. To obtain a good prediction performance,
the prediction results of “bad” state are revised by utilizing
the linear error prediction of ALRP. Similar to (10), the prediction
of future long-range error based on AR model with maximum
order \( q \) \((q < K)\) is recursively defined as
\[
\tilde{e}_n^b = \tilde{e}_{n-1}^b + \cdots + \tilde{e}_{n-q}^b = \sum_{j=0}^{q-1} \tilde{e}_{n-1-j}^b,
\]  (14)
Table 1: Computation complexities of AVSS-ALRP algorithms.

| Algorithms    | States | Multiplications | Additions |
|---------------|--------|-----------------|-----------|
| LRP           | "good" and "bad" | K               | K         |
| ALRP          | "good" and "bad" | 2K + 1          | 2K + 1    |
| VSS-ALRP      | "good"  | 4K + 8          | 4K + 3    |
|               | "bad"   | 2q + 4K + 9     | 3q + 4K + 4 |

where \( \hat{b}_n = [b_{n-1}^g, ..., b_{n-q}^g]^T \) are previous predicted errors of VSS-ALRP algorithm within a predicted "bad" state and \( d = [d_0^g, ..., d_{q-1}^g]^T \) are the AR coefficients vector for error prediction. The update equation of coefficients \( \hat{d} \) based on a fixed step-size \( \mu \) is expressed as

\[
\hat{d}_{n+1} = \hat{d}_n + \mu \hat{e}_n^g \hat{e}_n^b,
\]  

(15)

where \( \hat{e}_n^g \) is the error function obtained by \( \hat{e}_n^g = e_n^g - e_{n+1}^g \). By combining (10) and (14), the final result of channel prediction for a predicted "bad" state can be revised as

\[
\hat{b}_n = \hat{b}_{d(n-1)} + \hat{e}_n^g.
\]  

(16)

3.3. Algorithm Complexity Analysis. The complexity analysis of ALRP algorithm for three-state LMS channel model has been considered in [13]. Table 1 shows the computation complexities of AVSS-ALRP algorithms at time \( n+1 \) except for the optimal initial coefficients of AR model. As shown in Table 1, when the step-size is updated at time \( n+1 \), the number of multiplications and additions of VSS-ALRP algorithm increases by \( 2K + 7 \) and \( 2K + 2 \) compared with ALRP, respectively. In addition, the number of multiplications and additions of the prediction for future long-range error is \( 2q + 1 \) and \( 3q + 1 \) in the case of "bad" state, respectively. On the whole, the additional complexity of AVSS-ALRP algorithm is acceptable due to small maximum order of AR model.

4. Simulation Results

In order to test the validity of the proposed scheme, we employed Monte Carlo simulations to evaluate the performance of the proposed scheme based on the two-state LMS channel model. Correlation coefficient and mean square error (MSE) between the fading signals of predicted results and actual values (channel envelopes or gains) are used as prediction evaluation standard. A comparative analysis between the results predicted by the proposed algorithm and the existing scheme [10] is presented for intermediate tree-shadowed (ITS) environment at S-band and 60° satellite elevation. The simulation parameters are set up as follows. The extracted propagation parameters are listed in Table 2. Additionally, the fading signals correlation properties are directly related to the MSPE performance; namely, the MSE performance is improved with the increasing of correlation coefficient.

4.1. Prediction Performance of Channel Shadowing State. In this paper, the fading signals directly obtained through the proposed channel model are smoothed to get the prediction observed values; that is, smoothing average method is performed over the observation period with rate of \( f_s \). Figure 4 shows the correlation coefficient of the observed values for smoothing average and downsampling. The results in Figure 4 demonstrate that the smoothing average is remarkably superior to the downsampling, which is more beneficial to the long-range prediction of shadowing state.

The comparison of the channel shadowing state prediction errors of different methods is given in Table 3. Here, the mobi-le speed is fixed at \( v = 12.5 \text{ m/s} \) and the order of weighted prediction \( K = 3 \). The true state prediction error is approximately 0.3014 via (9). From Table 2 we can see that the prediction error of the eigenvalue decomposition combined with smoothing average (denoted as SD) is most close to the true value compared to others, and SD can be regarded as a more potential way to achieve state prediction than downsampling weighted prediction (DW).

4.2. Prediction Performance of Fading Signals. The correlation coefficient of SD and DW combined with the classical LRP algorithm [5] is given in Figures 5 and 6 under different signal-to-noise ratio (SNR) and mobile speed conditions. The fading signals’ correlation properties are directly related to the MSE performance; namely, the MSE performance is improved with the increasing of correlation coefficient.

In the two figures we observe that the correlation coefficient in all schemes is significantly improved with the increasing of SNR and tends to be convergent when the SNR is larger than 30 dB. We see that the correlation coefficient based on SD-LRP always outperforms DW-LRP in low to medium SNR.

Figure 4: Correlation coefficient of channel observed values.
Table 2: Propagation parameters for 60° elevation in its environment at S-band.

| States     | $M_A$ | $\sigma_1$ | $a_1$ | $\Sigma_A(\mu_2)$ | $\sigma_2$ | $a_2$ | $b_1$ | $b_2$ | $b_3$ | $\mu_3$ | $\sigma_3$ | MP |
|------------|-------|------------|-------|-------------------|------------|-------|-------|-------|-------|--------|------------|----|
| “good”     | -0.9914 | 0.3894 | 0.6458 | 1.6841 | 1.8242 | 0.0728 | 0.3421 | 0.3800 | -10.2 | 3.0840 |
| “bad”      | -5.2672 | 1.3666 | -0.0357 | -0.8572 | -1.3569 | 0.0203 | 0.3421 | 0.4190 | -10.0 | 1.4142 |

Table 3: Prediction error of channel states.

| Methods          | Weighted prediction | Eigenvalue decomposition |
|------------------|---------------------|-------------------------|
| Downsampling     | 0.3187              | 0.2960                  |
| Smoothing average| 0.3003              | 0.2923                  |

Figure 5: Correlation coefficient of various schemes with mobile speeds.

Figure 6: Correlation coefficient of various schemes with SNR.

Figure 7: SD-AVSS prediction of two-state LMS channel ($v = 12.5$ m/s, SNR = 25 dB).

In this paper, we maintain the MSE under a certain threshold to guarantee the overall channel prediction performance (see [7] for reference). The correlation properties and MSE performance related to the channel prediction of the DW-LRP, DW-AVSS, and the proposed SD-AVSS schemes are
obtained for the mobile speeds of 5 m/s and 10 m/s and given in Figures 8 and 9, respectively.

It is obvious that the proposed scheme has faster correlation convergence and better MES performance than DW-LRP scheme, and the MES performance is improved by approximately one order of magnitude. The correlation properties of the AVSS using approximate observed values obtained by smoothing average are superior to DW-AVSS but finally converge to the same level when SNR is higher than 25 dB. Besides, the prediction performance of slow movement is better than that of fast movement. The BER performance curves of the three schemes decline gradually with the increasing SNR. The reliability performance improvement of the proposed scheme is very significant at the cost of slightly higher computational complexity brought by error prediction.

5. Conclusion

A novel linear AVSS-ALRP scheme of LMS fading signals over the two-state channel model with variable propagation parameters has been proposed as a solution to the problem of prediction error and slow convergence in the classical LRP algorithm. Aiming at channel fading signals’ correlation and long transmission delay, we present the prediction of
long-range channel shadowing state based on SD method. Simulation results under different conditions show that the proposed scheme could not only predict the future long-range channel state and fading signals accurately and have a better performance in the aspects of MSE and correlation properties compared to the DW-LRP, but also have superiority in universal applicability over the LRP algorithm at the expense of increasing acceptable complexity. Moreover, the scheme in this paper can be extended to the prediction of single- and multisatellite LMS narrowband channel at S-band and is extremely applicable for the analysis of adaptive transmission performance in LMS communication systems.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This paper is supported by the National Natural Science Foundation of China (Grant no. 61403093), Science Foundation of Heilongjiang Province of China for Returned Scholars (Grant no. LC2013C22), Assisted Project by Heilongjiang Province of China Postdoctoral Funds for Scientific Research Initiation (Grant no. LHB-Q14048), and China Fundamental Research Funds for Central Universities (Grant no. HEUCFI40807).

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