Adaptive Rateless Coding Scheme for Deep-Space Ka-Band Communications

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Abstract—The deep-space Ka-band channels are very sensitive to the weather conditions of the ground station area, where the data link will be suffered by high dynamic bit error rate and even occurred random interruption. Moreover, the huge distance of the deep-space communications caused that the transmitter can only have delayed channel state information (CSI) feedback. We modeled the noise temperature of the Ka-band link as an $N$-state Markov model based on the Autoregressive (AR) analysis in this paper, and then proposed a low-error channel state estimation algorithm. Furthermore, we designed an adaptive rateless coding scheme based on Analog fountain codes (AFC), which is capable to adjust code-rate to maximize the usage of the Ka-band link. Simulation results show that the proposed scheme have capacity-approaching performance, can increase system throughput and improve transmission efficiency.

Index Terms—Deep-space communications; Ka-band; $N$-Markov model; Autoregressive analysis; Analog fountain code.

I. INTRODUCTION

With the development of deep-space explorations and the evolution of future Interplanetary Internet communications, the increasingly demand on transmission capacity, such as higher data rate and wilder bandwidth, is the primary issue to be addressed. The Mars Reconnaissance Orbiter (MRO) demonstrated the availability and feasibility of the 32 GHz Ka-band for the future exploration missions.

The Ka-band link has much more available bandwidth, which can significantly increases the downlink throughput. [1] show that the comparison of X-band and Ka-band data transfer rate between Mars orbiter to Canberra deep-space station in a two year period, file delivery from the Ka-band link have reached an order of magnitude higher than the X-band link. However, Ka-band links are highly vulnerable to the weather conditions of the ground station area. As we compared in the similar communication situations [2], if 1 dB loss due to weather impairments at X-band channel, then the Ka-band channel would be suffered approximately of 4 dB loss. Furthermore, there are 3~4 dB attenuation in cloudy days and 10~50 dB attenuation in rainy days. Whenever the 50 dB attenuation is occurred, the communication systems cannot perform normally data transmission. At the same time, Ka-band links will be randomly interrupted due to the effect on rainfall. The power compensation method can no longer used here because the power limitation of space transmitter. Besides, the characteristics of huge propagation delay makes the convolutional Automatic Repeat-reQuest feedback cannot be used in deep-space [3], [4]. Therefore, we first need to build an accurately model to predict rainfall events to deal with time-varying channel state.

On the other hand, several researches focused on the channel state prediction algorithms and tried to obtain optimal data transmission policy, by carefully allocated the long-term power to enhance the total channel signal-to-noise ratio (SNR) [5], and then adjust their transmit data rate during the transmission, or even code rate and so on [6]. From the adaptive erasure coding perspective, it is more meaningful to predict the weather state for the code rate adaption in the transmit end [7], [8]. As a general method, Markov model could be exploited to describe the Ka-band link state [9]. However, the high forecast error in this model cannot meet the requirement of reliability data transmission in some deep-space missions.

In this paper, we put forward to design a “prediction + coding” adaptive transmission scheme. In Section II, we propose a $N$-Markov chain to model the rain attenuation, and use the AutoRegressive (AR) model to forecast rain attenuation, which the prediction error may control in ±2 dB. Then, in Section III, we introduce the Analog Fountain Code (AFC) [10], and optimized the AFC scheme to satisfy our Ka-band communications in Section IV. In Section V, Simulation results show that the AFC scheme can reduce the sensitivity of the prediction error of the Ka-band $N$-Markov model, and the error can be controlled in less than ±2 dB, the AFC decoding BER fluctuation is less than $2^{-5}$. Finally, Section VI concludes the paper.

II. ANALYSIS OF RAIN ATTENUATION ON KA-BAND

A. Modeling of Rain Attenuation on Ka-band

In the beginning, we design a $N$-Markov chain, which is proposed by the multi-state Markov chain theory. In this model, the behaviors of the channel state transforming is divided into $N$ states and each state represents an attenuation value, the duration and slope of the rain fading can be arbitrarily adjusted. The transition probability between the states are decided by Van DE Kamp Slope Model [11]. This model can simulate the rainfall events in accordance with the systems requirements, thus it is flexible and widely used in the
rain attenuation research and application fields. The fade slope distribution decided by the attenuation $A(t)$, time interval $\Delta t$ and a low-pass filter which the cutoff frequency is 3 dB, which can filter out the troposphere shine and rapid change of rain fading. After been filtered, the fade slope $\xi$ in a certain time point is defined as follows:

$$\xi(t) = \frac{A(t + \frac{1}{2}t) - A(t - \frac{1}{2}t)}{t},$$  

(1)

Conditional probability density function of the fade slope can be obtained by Van DE Kamp fade slope model, and the calculation steps are shown as follows:

**First stage**: calculate the function $F(f_B, \Delta t)$:

$$F(f_B, \Delta t) = \sqrt{\frac{2\pi^2}{1/f_B^2 + (2\Delta t)^2}},$$  

(2)

where, $f_B=0.2$ Hz, $b=2.3$.

**Second stage**: count the standard deviation $\sigma_\xi$ of fade slope $\xi$ on the certain point:

$$\sigma_\xi = sF(f_B, \Delta t)A (dB/s),$$  

(3)

where $s=0.01$.

**Third stage**: we then solve the conditional probability density function $P(\xi \mid A)$, where $A$ is the fade value, and we have:

$$p(\xi \mid A) = \frac{2}{\pi\sigma_\xi(1 + (\xi/\sigma_\xi)^2)^{1/2}},$$  

(4)

**Fourth stage**: count complementary cumulative distribution about conditional probability function $P_c(\xi \mid A)$.

$$P_c(\xi \mid A) = \frac{1}{2} - \frac{\xi/\sigma_\xi}{\pi(1 + (\xi/\sigma_\xi)^2)} - \frac{\arctan(\xi/\sigma_\xi)}{\pi},$$  

(5)

By using the calculation results of formula (4) and (5), fade slope condition probability density function and complementary cumulative distribution function are obtained, as shown in Fig. 1 and Fig. 2, respectively.

Fig. 1 and Fig. 2 show that the fade slope follows the normal distribution, and as attenuation value became smaller, it has steeper curve. It indicates that the smaller the attenuation value is, the probability of “jump to other attenuation value” decreases lower, and the rain fading is more stable. Similarly, when the attenuation value increases, the curve become more gently, and the higher probability of “jump to other attenuation value”, and the rain fading is unstable. This results show that the little rain has higher probability to transition their rain attenuation value, and when the rain is very heavy, the rain attenuation value will have less probability to transition.

We then can use the $N$-Markov theory to build our short duration rain fading time-sequence model. For a rainfall duration, this model can produce adequate rainfall events according to the given duration and maximum fading depth. If the maximum of fading depth is $A_{max}$, the minimum value is $A_{min}$, and the fade interval is $\Delta a$, then the rain fading probability distribution can be denoted as an $N$ order transition probability matrix $P$, in which each element $p_{ij}$ in $P$ represents the probability of a rain fading value $A_i$ transition to the rain fading value $A_j$:

$$P = \begin{pmatrix}
p_{11} & p_{12} & \cdots & p_{1N} 
p_{21} & p_{22} & \cdots & p_{2N} 
\vdots & \vdots & \ddots & \vdots 
p_{N1} & p_{N2} & \cdots & p_{NN}
\end{pmatrix}$$

If $\xi$ is known, the above transition probability matrix $P$ can be calculated by (4), and the schematic diagram is shown in Fig. 3.

Now we can calculate the probability $p_{ij}$, let $\xi_k = (A_{i+k} - A_i)/2$, and $p_{i,i+k}$ represents the value of $P(\xi_k = (A_{i+k} - A_i)/2 \mid A_i)$, where $j = i \pm k$, we have:
Fig. 4: Rain fading records on 35.2 GHz in Xi’an, China, March 14, 2010.

Fig. 5: N-Markov chain simulation results.

$$P_{i,k} = \int_{kda-da/2}^{kda+da/2} P(\xi | A) d\xi, \quad k \in [0, k_{\text{max}}].$$  

where, $k_{\text{max}} = \xi_{\text{max}} \cdot \Delta t/da$.

Therefore, (6) can be used to calculate the transition probability of N-Markov chain in each state, which can solve the state transition matrix $P$, then we can produce the corresponding rainfall time-sequenece series. Fig. 4 shows the measured rain fading time-series value on 35.2 GHz in Xi’an, China, March 14, 2010. The biggest fading depth value is 8 dB, and our N-Markov chain simulates result is shown in Fig. 5.

However, rainfall is always treated as a random process, our N-Markov model cannot produce the rain fading values which are completely as same as the actual weather. But the difference between our model and the real data is little, as compare the probability distribution of the measured rain fading time-sequenece series and simulated series in Fig. 6, we can make our N-Markov chain mode to be useful with some complementary in the next subsection.

B. Forecasting Method for Rain Attenuation on Ka-band

The fading channel prediction researches mainly focus on the linear prediction algorithms. In this paper, we use AR model to solve the Ka-band deep-space communication rain fading value forecasting. First, we need determine the order number, by using the Final Prediction Error (FPE) criterion. The FPE method is using the variance of one-step model, and it can forecast error to determine the applicable order of AR model. If the variance is small, the model can fitting better performance. The FPE criterion is defined by:

$$\text{fpe}_p = \hat{\sigma}^2 \frac{n + p}{n - p},$$  

where $\hat{\sigma}^2$ is the variance of forecast error.

Assumed there are $p$ measured historical data before time 0:

$$x(n-\Delta t), x(n-2 \Delta t), \ldots x(n-p \Delta t)$$

where $\Delta t$ is forecast time interval, and the rain fading value at time 0 and time 0 + $\Delta t$ as follows:

$$\begin{align*}
\hat{x}(n) &= -a_1 \cdot x(n-\Delta t) - a_2 \cdot x(n-2 \Delta t) - \ldots - a_p \cdot x(n-p \Delta t) - \\
\hat{x}(n+\Delta t) &= -a_1 \cdot x(n) - a_2 \cdot x(n-\Delta t) - \ldots - a_p \cdot x(n-(p-1) \Delta t)
\end{align*}$$  

Each coefficient can be determined by the following equations:

$$\begin{align*}
r_{xx}(m) + \sum_{i=1}^{p} a_i \cdot r_{xx}(m-i) &= 0 \\
r_{xx}(0) + \sum_{i=1}^{p} a_i \cdot r_{xx}(i) &= \sigma^2
\end{align*}$$  

where $r_{xx}(m)$ is autocorrelation function of the historical data.

We use the measured historical data mentioned before, then we can get the FPE order number which is 3. Therefore, we can establish a third order AR prediction model, the prediction error result is shown in Fig. 7. In our AR (3) prediction model, the maximum error is less than 2 dB, and average error is $8.104 e^{-7}$, which is achieved a good prediction effect.
Fig. 7: Comparison of real date and predicted date by AR(3).

III. ANALYSIS AND DESIGN OF ADAPTIVE ANALOG FOUNTAIN CODES

A. Analog Fountain Coding and Decoding

1) Analog Fountain Coding: Same as the convolutional binary rateless coding schemes, analog fountain code first selects an integer $d$ as coding degree, the integer degree value get from an advance designed degree distribution; Next, randomly selects $d$ variable nodes, multiplied by the real weight, respectively, and then adds them together. The real weight is from an advance designed weight set $W_s$. Each code symbol is generated as follows

$$S_j = \sum_{i=1}^{d} w_{j,i} b_{j,i}$$

where $w_{j,i} \in W_s$, $b_{j,i}$ is the $i$th selected variable node. Therefore, after we get $N$ coded symbols, we can derived the matrix form from (10)

$$S = Gb$$

where $G$ is $N \times k$ generator matrixthe number on $i$th line, $j$th column of $G$ is the weight value in AFC coding process of the check node $j$ that $i$ participate in.

2) Analog Fountain Decoding: In this paper, we select a BP decoding algorithm with a modified version for AFC decoding, called compression perception BP (CSBP) decoding algorithm, to adapt to the rate variable encoding scheme which is put forward. The CSBP decoding algorithm is detailed in [12].

Then, with the CSBP decoding algorithm, and we assumed degree is fixed as $d = 8$, and the weight set is $W_s = \{\pm 4, \pm 3, \pm 2, \pm 1\}$. The simulation result is shown in Fig. 8, which is verified the CSBP decoding algorithm can provide a good decoding performance with finite code-length in Ka-band channels.

B. Optimization of AFC Degree Distribution and Weight Set

In the practical applications, the influence of degree distribution to the AFC performance is important, when the average degree increases, it can get a lower bit error rate with the decoding complexity increases. On the other hand, to ensure the efficiency of transmission power in deep-space communications, we need design a weight set which can lead the weight distribution of coded packets to be as closer as to the Gaussian distribution. Therefore, we choose the weight set transform from $\{1, 2, 4, 4\}$ to $\{1, 2, 3, 4\}$, which can produced more Gaussian-like distribution. Furthermore, we combine with the thought that, a coding linear equation $\sum_{i=1}^{d} b_{j,i} w_{i} = s_j$ can only have one numerical solution since $s_j$ are identical and independent random variables, then we propose a new weight set optimum conditions

$$\sum_{i=1}^{d} b_{j,i} w_{i} = s_j = 0$$

where $n_i \in \{0, 1\}$ and $I_i \in \{0, 1\}$. Then we have the optimum weight set: $w_s = \{1/2, 1/3, 1/5, 1/7, 1/11, 1/13, 1/17, 1/19\}$

Through the simulation results shown in Fig. 9, we can verify that the decoding performance can be further improved with optimum weight set in high SNR region.

C. Complexity of Coding and Decoding

Although the AFC coding scheme can improve the data transmission in Ka-band communications, we need consider the complexity. We analysis the complexity of our scheme from two aspects, encoding and decoding. Assumed that $R$ and $L$ is the maximum number of nonzero elements in the generated Matrix of each column and row, respectively. The complexity of produce the generator matrix is $O(R \cdot N)$. As each encoded symbol connected with $L$ variable nodes at
most, the generation of the code symbol can be calculated by querying a table size of $2^L$. In this way, the complexity of generating $M$ codes is $O(M)$.

As we adopt BP algorithm for the AFC scheme, in each iteration, the upper bound of the operation cost is a $O(R \cdot W)$, where $W = 1 + \sum_{i=1}^{L} w_i$. So the total complexity of the CSBP decoding is $O(R \cdot N \cdot W)$. For a designed AFC scheme, $W$ and $R$ is constant, so our AFC scheme can be considered to have linear computation complexity.

D. Analysis of Channel Estimation Accuracy

The prediction error is always exist, but with the analysis aforementioned, the forecast error can be controlled in ±2 dB. Assume the code length is 100, code-rate is 5/4, and 1000 packets have been transmitted. We simulate the BER performance of this coding scheme in the error range from -2 dB to 2 dB on typical SNR: 10 dB, 15 dB, 20 dB, 25 dB and error variance on the certain point, the results are shown in Fig. 10. Obviously, the AFC scheme joined with adaptive transmission can adapt to the unexpected errors in Ka-band link as shown in Fig. 10, and the AFC scheme is not sensitive to the prediction error. So we update the adaptive rate transmission scheme to further improve the link throughput.

IV. SIMULATION RESULTS

We assume that a fixed degree of 8 and the weight set is $w_s = \{1/2, 1/3, 1/5, 1/7, 1/11, 1/13, 1/17, 1/19\}$ in coding process. Fig. 11 shows the link throughput of transfer using adaptive code scheme in AWGN channel versus the SNR with $k = 10^7$ bits and BER=10⁻⁴. We can see the link throughput can approach the Shannons limit in a wide SNR range. Fig. 11 also shows that the throughput of LDPC codes with various modulation, the length of LDPC code symbol is 648 bits. From Fig. 11, we can find that LDPC code has small dynamic range, and the performance is inferior to Adaptive-AFC. Besides, LDPC codes are rate-fixed and only can applied in certain value of SNR, which is difficult to satisfy the requirements of deep-space Ka-band communications.

V. CONCLUSION

In this paper, we proposed an adaptive predict coding scheme that can adapt to the channel conditions and without the exactly knowledge of channel state information. Our AR(3) $N$-Markov prediction mechanism can reduce the prediction error probability and limit in a certain error range. Based on this prediction method, we adopt AFC to design a adaptive coding scheme which is not sensitive to the forecasting error, and the simulation results show that our adaptive rateless coding scheme is much higher than fixed rate LDPC schemes.

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Fig. 10: Impact of inaccurate SNR estimation.

Fig. 11: Link throughput of adaptive-AFC.