QPSK System Performance Using Fading Identification Circuit

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Abstract – **In this paper we consider performance evaluation of QPSK transmission system operating in a frequency nonselective fading channel in the persence of QPSK interference. A algorithm that combines decision feedback and adaptive linear prediction (DFALP) [1] by using tentative coherent detection is used for tracking the phase and amplitude of the fading channel. The channel gain is predicted by adaptive linear predictor employing LMS algorithm, by Kalman filter and by smoother. It will be shown that system employing Kalman filter has the best performance, as expected, over wide range of system, channel and interference parameters.**

Keywords – **fading channels, adaptive filtering, channel identification**

I. Introduction

To detect an information sequence transmitted coherently and reliably over a fading channel, it is necessary to estimate the channel phase and amplitude. This is motivated by the fact that coherent detection of signals over fading channels is superior to non-coherent detection if accurate channel state information (CSI) is available.

One approach was proposed by Moher and Lodge [2] to track frequency nonselective fading channels, where one training symbol is sent for every $K_t - 1$ data symbols, and linear interpolation is used to estimate channel gains. This idea was extended by Irvine and McLane [3] using decision-feedback and noise smoothing filters. However, such filtering results in large decision delay.

It is well-known that fading channels are correlated. Therefore, past channel gain estimates may be used to predict the channel gain using linear prediction theory. This paper investigates fading channel amplitude and phase prediction in the presence of QPSK interference. Three different predictors are used: adaptive linear predictor employing LMS algorithm, Kalman filter, and smoother.

It should be noted that a non-adaptive linear predictor was used by Young and Lodge [4]. However, the algorithm reported in [4] may not outperform a conventional differential detector when the signal to noise ratio (SNR) is less than 20 dB.

In the next Section, we review the fading channel model, and describe the DFALP algorithm using both predictors. Simulation results are presented in Section III.

II. Fading Channel Model

Let I_k denote a binary information sequence, and x_k a low-pass equivalent discrete-time output of the encoder/modulator. The complex signal x_k is transmitted over a frequency-nonselective Rayleigh or Rician fading channel. The received low-pass equivalent discrete-time signal is then

$$y_k = x_k c_k + i_k c_{I_k} + n_k \tag{1}$$

where i_k is complex QPSK interference, c_k, and c_{I_k} are channel gains, complex Gaussian processes with memory. The mean of c_k is $a = Ec_k$. When $a = 0$, the fading channel is Rayleigh. Otherwise it is Ricean. The covariance function of c_k, is

$$r_{k,k-n} = r_n = E\{(c_k - a)(c_{k-n} - a)^*\} \tag{2}$$

in general case. A special case of the above model is the Jakes-Reudink fading channel with r_n given by

$$r_n = r_0 J_0(2\pi f_m n T) \tag{3}$$

where $J_0()$ is the zeroth order Bessel function, T is the symbol period and f_m is the maximum Doppler frequency given by $f_m = v/\lambda$, with v and λ defined as mobile vehicle speed and transmission wavelength, respectively.

The the channel gain c_k, can be divided into two parts: the line-of-sight (LOS) part with average power a^2 and the random scattering part with average power r_0. The K factor is defined as the ratio $K = a^2/r_0$. If r_0 is normalized to 1, then $K = a^2$. The K factor is equal to zero for Rayleigh fading channels and is greater than zero for Rician fading channels. The average signal-to-noise (SNR) ratio per symbol is then

$$\gamma_s = \frac{a^2 + r_0}{\sigma_n^2} \tag{4}$$

where σ_n^2 is the variance of the additive white Gaussian noise (AWGN) n_k.

We now describe the algorithm using decision feedback and adaptive linear prediction (DFALP) [1] to track frequency nonselective (flat) fading channels. If x_k is a known training symbol and if the signal-to-noise ratio (SNR) and signal-to-interference ratio (SIR) are high, a good estimate of c_k can be easily computed as

$$c_k = \frac{y_k}{x_k} = \tilde{c}_k \tag{5}$$

according to Eq.(l), where y_k is the received signal. However, most of the received symbols are not training symbols.

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In these cases the available information for estimating c_k can be based upon prediction from the past detected data-bearing symbols $\bar{x}_i$ $(i < k)$. Since a fading channel is usually correlated, it is possible to use an adaptive linear filter to estimate the current complex channel gain c_k using the past detected symbols $\bar{x}_i$ $(i < k)$ and the current observed signal y_k.

The block diagram of the receiver is shown in Fig. 1.

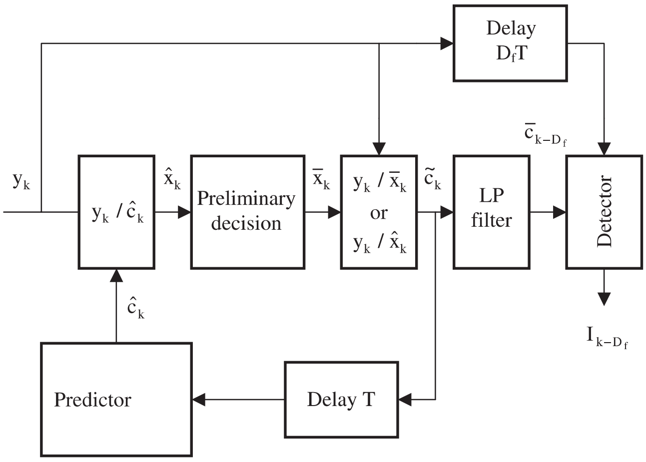

Fig. 1. Receiver block diagram

First, we estimate the data symbol using the predicted channel gain

$$\hat{x}_k = \frac{y_k}{\hat{c}_k} \tag{6}$$

where y_k, is the current received signal plus noise, and $\hat{c}_k$ is a channel estimate given by the linear predictor. Second, we use the minimum distance decision rule

$$\min_{x_k \in D} |\hat{x}_k - x_k| \tag{7}$$

where D is the signal constellation of the modulated complex low-pass equivalent signal x_k. For QPSK, $D = \{e^{jn\pi/4}, n = 1, 3, 5, 7\}$. Let $\bar{x}_i$ denote the detected data symbol, i.e.,

$$|\hat{x}_k - \bar{x}_k| = \min_{x_k \in D} |\hat{x}_k - x_k| \tag{8}$$

Using the detected data symbol $\bar{x}_k$, we formulate a new estimate of the channel gain

$$\frac{y_k}{\bar{x}_k} \tag{9}$$

There exist two possibilities for the decision rule (8). One possibility is that the decision is correct, i.e., $\bar{x}_k = x_k$. Then the estimate $y_k/\bar{x}_k$ would be reliable. On the other hand, if the decision is wrong, i.e., $\bar{x}_k \neq x_k$, the estimate $y_k/\bar{x}_k$ will certainly be very poor. To solve this problem, we use a thresholding idea. In most cases, if the decision is correct, the distance between the predicted channel gain $\hat{c}_k$ and the decision feedback estimate $y_k/\bar{x}_k$ would not be large, i.e., the probability that $|\hat{c}_k - y_k/\bar{x}_k| < \beta$ would be high, where β is a chosen threshold. On the other hand, if the decision is wrong, the distance between the predicted channel gain $\hat{c}_k$, and the decision-feedback estimate $y_k/\bar{x}_k$ would be large, i.e., the probability that $|\hat{c}_k - y_k/\bar{x}_k| > \beta$ would be high. Therefore the corrected channel estimate may be expressed as

$$\tilde{c}_k = \begin{cases} y_k/\bar{x}_k & |\hat{c}_k - y_k/\bar{x}_k| < \beta \\ \hat{c}_k & |\hat{c}_k - y_k/\bar{x}_k| \geq \beta \end{cases} \tag{10}$$

There exists no analytical approach to choosing the threshold β. In our experiments we determined optimal value for the threshold β to be 0.7 for all predictors.

The predicted fading channel gain, for adaptive linear predictor with LMS algorithm, at time k is

$$\hat{c}_k = \sum_{i=1}^{N_{LMS}} b_i^* \tilde{c}_{k-i} \tag{11}$$

where

$$(\tilde{c}_{k-1}, \tilde{c}_{k-2}, ..., \tilde{c}_{k-N})^T = \tilde{\boldsymbol{c}}(k) \tag{12}$$

is a vector of past corrected channel gain estimates and

$$(b_1, b_2, ..., b_N)^T = \boldsymbol{b}(k) \tag{13}$$

are the filter (linear predictor) coefficients at time k. The superscript T stands for transpose. The constant N_{LMS} is the order of the linear predictor. The LMS algorithm computes the filter coefficients $\boldsymbol{b}(k+1)$ of the next time-step using the current filter coefficients $\boldsymbol{b}(k)$ and the estimation error $\tilde{c}_k - \hat{c}_k$. Formally, the algorithm is

$$\boldsymbol{b}(k+1) = \boldsymbol{b}(k) + \mu(\tilde{c}_k - \hat{c}_k)^* \tilde{\boldsymbol{c}}(k) \tag{14}$$

where μ is the adaptation parameter controlling the convergence rate and steady-state error of the algorithm.

In case of Kalman filter, prediction is done in the following manner

$$\hat{c}_{tmp} = \rho \hat{c}_k \tag{15}$$

$$M_{tmp} = \rho^2 M_k + (1 - \rho^2) \tag{16}$$

$$K = \frac{M_{tmp}}{\sigma^2 + M_{tmp}} \tag{17}$$

$$\hat{c}_{k+1} = \hat{c}_{tmp} + K(\tilde{c}_k - \hat{c}_{tmp}) \tag{18}$$

$$M_{k+1} = (1 - K) M_{tmp} \tag{19}$$

The smoother predicts next channel gain as the average value of the pervious channel gains:

$$\hat{c}_k = \frac{1}{N_s} \sum_{i=1}^{N_s} \tilde{c}_{k-i} \tag{20}$$

where N_s is the smoother length.

The corrected channel estimate $\tilde{c}_k$ is then low-pass filtered using a linear phase low-pass filter (LPF) with $2D_f + 1$ taps to reduce the noise. That is, the final channel gain estimate is

$$\bar{c}_{k-D_f} = \sum_{i=0}^{2D_f} h_i \tilde{c}_{k-i} \tag{21}$$

where h_i is the impulse response of a LPF with $2D_f + 1$ taps. The filter cutoff frequency is equal to Doppler frequency.

III. Numerical Results

In following figures we simulated a typical digital cellular telephone channel, where the carrier frequency is 800 MHz, symbol rate is 24000 symbols/sec, and the fading channel is Rayleigh. The low-pass filter length is set to $D_f = 10^3[-7.526(f_mT)^3 + 3.6729(f_mT)^2 - 0.3981(f_mT) + 0.0153]$, which is determined in [1] to be optimal. The interference rate is the same as the rate of useful signal.

Figure 2. shows the error probability of the system using adaptive linear predictor with LMS algorithm as a function of LMS algorithm length. Signal to interference ratio is set to SIR = 20 dB. It can be seen that for high receiver speed (curve b) a optimal value for filter length is $N_{LMS} = 2$. For low receiver speed (curve a) optimal value is $N_{LMS} = 4$. However, minimal error probability is only slightly lower than the error probability for $N_{LMS} = 2$. Because of this fact we chose $N_{LMS} = 2$ for all the following simulations due to simplicity of the receiver.

Error probability as a function of smoother length is shown in Fig. 3. The error probability depends on the smoother length in similar way as in Fig. 2. So, similar conclusions can be made, and we chose $N_s = 2$ for all the following simulations.

Figure 4. shows the error probability as a function of the receiver speed for all the three predictors. On can see that Kalman filter has the best performance regardless of signal to interference ratio and receiver speed. Since it is a optimal structure, the error probability increases with the receiver speed. On the other hand, smoother and LMS algorithm filter are not optimal structures and they have the best performance for particular receiver speed and SIR, i.e. their parameters are best suited for one combination for receiver speed and SIR. Therefore, in order to have the best performance, smoother and LMS algorithm filter should change its parameters, such as length and adaptation factor, adaptively, which can be very difficult.

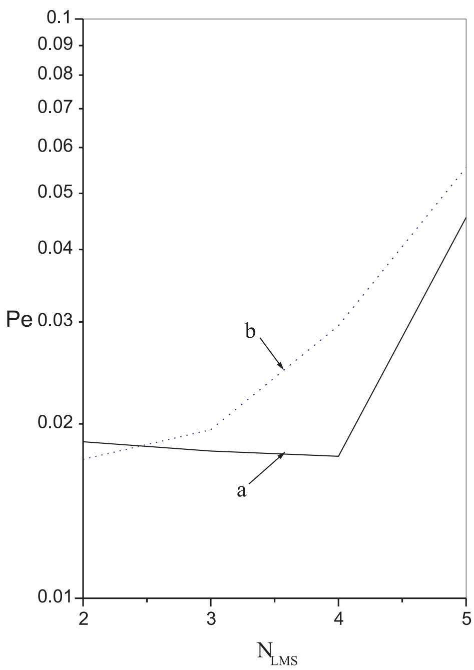

Fig. 2. Error probability as a function of LMS algorithm length: a – $v = 5$ km/h, b – $v = 50$ km/h

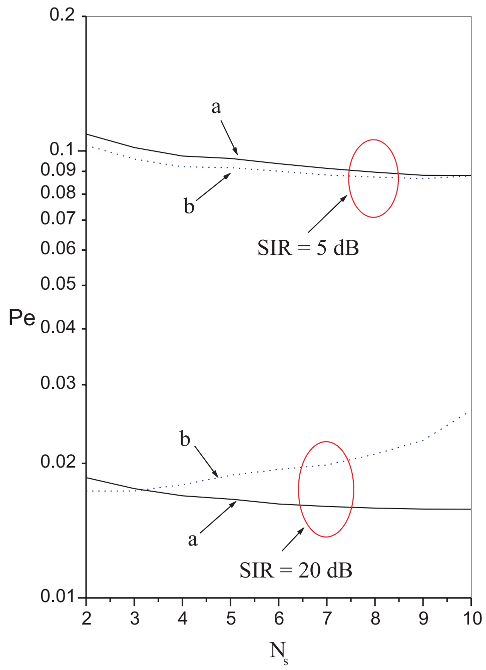

Fig. 3. Error probability as a function of smoother length: a – $v = 5$ km/h, b – $v = 50$ km/h

Error probability as a function of signal to interference ratio is shown in Fig. 5. Kalman filter again has better performance than the other two predictors. For high SIR, smoother and LMS algorithm filter have the same error probability. If

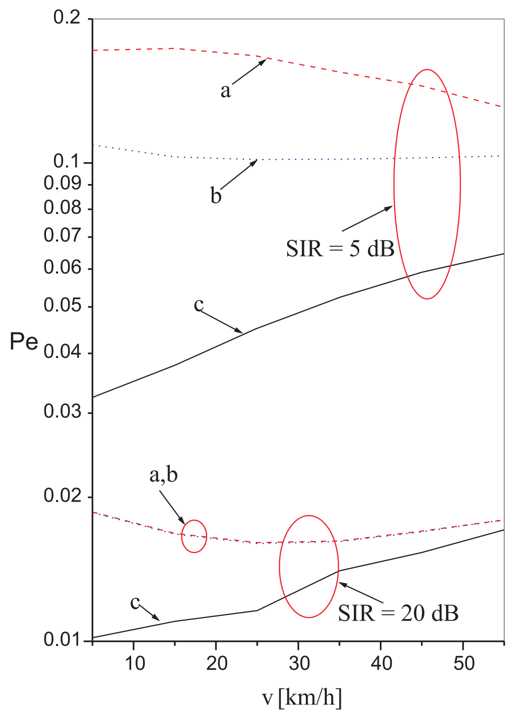

Fig. 4. Error probability as a function of receiver speed: a – LMS algorithm, b – smoother, c – Kalman filter

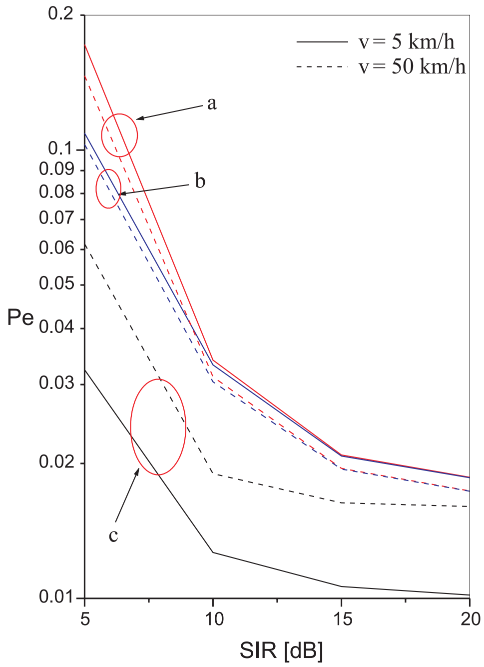

Fig. 5. Error probability as a function of signal to interference ratio: a – LMS algorithm, b – smoother, c – Kalman filter

we consider the influence of receiver velocity, the same conclusions can be made as in Fig. 4.

IV. Conclusion

In this paper we considered performances of QPSK transmission system operating in a frequency nonselective fading channel and in the presence of QPSK interference. The channel gain is predicted by adaptive linear predictor employing LMS algorithm, Kalman filter, and smoother. It was shown that both LMS algorithm and smoother length may be set to 2 since the error probability for this length is not much higher than the minimal error probability. Kalman filter is a optimal structure and has the best performance, as expected. On the other hand, smoother and LMS algorithm filter are not optimal structures and, in order to have the best possible performance, they should change its parameters, such as length and adaptation factor, adaptively, which can be very difficult.

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