Joint Data and Kalman Estimation of Fading Channel Using A Generalized Viterbi Algorithm

M. Javad Omidi, S. Pasupathy, *Fellow, IEEE*, and P. G. Gulak, *Member IEEE*
Department of Electrical and Computer Engineering
University of Toronto, 10 King's College Road, Toronto, Ontario M5S 3G4, Canada
E-mail: omidi@eecg.toronto.edu, Tel: (416) 978-1652, Fax:(416) 971-2286

Abstract—This paper presents a method of sequence estimation using joint data and channel estimation for the frequency selective Rayleigh fading channel. To detect the transmitted data sequence, a generalized Viterbi algorithm is employed in which each trellis branch metric is computed based on an estimation of the channel impulse response. The information from the survivor path estimator is passed to the next branch for the next channel estimate. A linear model is used for the fading channel. An ARMA representation for the channel is derived, making it possible to employ the Kalman filter as the best estimator for the impulse response of the channel. For IS-54 formatted data transmission the results obtained with the Kalman filter are shown to be superior to those of other existing methods.

1. Introduction

MLSE is the optimum detection method for data signals received over a frequency-selective multipath fading channel. Various kinds of MLSEs are introduced to combat the degradation of error performance due to the severe ISI in fast fading channels [1] [2] [3]. MLSE is implemented using the Viterbi algorithm (VA) to reduce its complexity and generally all versions of MLSE receivers require estimates of the channel impulse response (CIR).

An inherent difficulty associated with applying the estimation methods is that the unknown transmitted data is required for the estimator adaptation. In the "decision directed mode" the actual transmitted data, which is not available at the receiver a priori, is replaced by an estimate of the data stream. However, there is usually a "decision delay" inherent in the VA, that causes poor tracking performance. To reduce the effects of this estimation delay three main procedures have been developed [4]. One method uses a fixed delay VA [5] but it suffers from degradation in tracking due to the existing decision delay. The second method estimates CIR by an adaptive decision feedback equalizer (DFE) without any delay in decision [6], but the error propagation problem has a serious effect on the BER performance.

The third approach [2][4][7] is an adaptive MLSE in which the CIR is estimated along the surviving paths associated with each state of the trellis. Each surviving path maintains its own estimate of the channel based on the hypothesized transmitted data sequence. This method eliminates the decision delay and its performance is superior to other methods. In this method channel estimation is usually performed via LMS or RLS algorithms in a generalized VA and the performance of the receiver strongly depends on how well the estimator can track the rapid changes of the CIR in the fast fading conditions.

In this paper we are concerned with differentially coherent detection of DQPSK signals over frequency selective Rayleigh fading channels. We assume a linear time-varying model for the channel and we obtain a new ARMA representation for the CIR based on the channel parameters. This model gives more information about the channel at the receiver compared to what is reported in similar algorithms. We have considered a communication system, very similar to that described in the IS-54 standard, where digital data signals are packed into TDMA blocks starting with a preamble training sequence.

This paper is organized as follows. Following a short overview of the mobile communication system under consideration in section 2, we present a model for the channel and derive the ARMA representation for the CIR in section 3. In section 4, we introduce the formulation of the Kalman filter and RLS algorithm. The joint data and channel estimation algorithm based on using a set of Kalman filters is described in section 5, and simulation results are presented in section 6. Finally concluding remarks are given in section 7.

2. The Communication System

In the North American narrowband TDMA standard (IS-54), the $\pi/4$ -shifted DQPSK technique is employed. We consider a DQPSK signaling scheme instead, which should not lead to a significant difference in performance. The simplified baseband equivalent system is shown in Fig. 1. The data sequence $\{a_i\}$, with symbol period T, is input to a filter whose impulse response, $f(t)$, has the bandlimited raised-cosine spectrum. The transmitted signal is:

$$s(t) = \sum_i a_i f(t-iT). \tag{1}$$

The equivalent low-pass time-variant impulse response of a frequency selective Rayleigh fading channel, $c(t,u)$, represents the channel response at time t due to an impulse applied at time $t-u$. $c(t,u)$ is usually modeled as a wide-sense stationary uncorrelated scattering process.

It is assumed that the receiver samples the incoming signal at the rate $T=\alpha T_s$ and by redefining the information sequence as

$$b_k = \begin{cases} a_{k/\alpha} & \frac{k}{\alpha} \, integer \\ 0 & otherwise \end{cases} \tag{2}$$

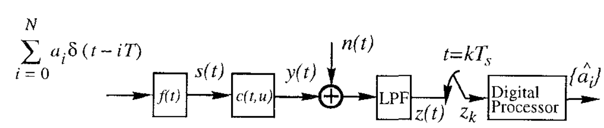

Fig. 1: The Signal Model for the communication system.

0-7803-3250-4/96$5.00©1996 IEEE

the sampled signal, z_k, can be written as

$$z_k = \sum_{i=0}^{\beta} b_{k-i} h_{k,i} + n_k \tag{3}$$

where $h_{k,i}$ is the impulse response of the equivalent channel at time k due to an impulse that was applied i time units earlier, it describes both $f(t)$ and $c(t,u)$ blocks of Fig. 1 in the discrete time domain [1], and its total length is $(\beta+1)$. The LPF is assumed to have a flat frequency response in the transmission band, and n_k is additive white Gaussian noise.

To derive the state space model for the channel consider the $(\beta+1)$ dimensional complex Gaussian random vector at sampling time k

$$\boldsymbol{h}_k = (h_{k,0}, h_{k,1}, \ldots, h_{k,\beta})^T \tag{4}$$

and define the states of the state-space model as a vector composed of r subsequent impulse responses

$$\boldsymbol{x}_k = (\boldsymbol{h}_k, \boldsymbol{h}_{k-1}, \boldsymbol{h}_{k-2}, \ldots, \boldsymbol{h}_{k-r+1})^T \tag{5}$$

$\boldsymbol{h}_k$ is a wide-sense stationary Gaussian random vector and has an autoregressive moving average (ARMA) representation:

$$\boldsymbol{h}_k = \boldsymbol{F}_1 \boldsymbol{h}_{k-1} + \ldots + \boldsymbol{F}_r \boldsymbol{h}_{k-r} + \boldsymbol{G}_o \tilde{\boldsymbol{w}}_k + \ldots + \boldsymbol{G}_m \tilde{\boldsymbol{w}}_{k-m} \tag{6}$$

The vector process $\boldsymbol{x}_{k+1}$ can be written as:

$$\boldsymbol{x}_{k+1} = \begin{bmatrix} \boldsymbol{F}_1 & \boldsymbol{F}_2 & . & . & \boldsymbol{F}_r \\ \boldsymbol{I} & 0 & . & . & 0 \\ 0 & \boldsymbol{I} & . & . & 0 \\ . & . & . & . & . \\ 0 & 0 & . & \boldsymbol{I} & 0 \end{bmatrix} \boldsymbol{x}_k + \begin{bmatrix} \boldsymbol{G}_0 & \boldsymbol{G}_1 & . & . & \boldsymbol{G}_m \\ 0 & 0 & . & . & 0 \\ 0 & 0 & . & . & 0 \\ . & . & . & . & . \\ 0 & 0 & . & . & 0 \end{bmatrix} \begin{bmatrix} \tilde{w}_k \\ \tilde{w}_{k-1} \\ . \\ . \\ \tilde{w}_{k-m} \end{bmatrix} \tag{7}$$

or

$$\boldsymbol{x}_{k+1} = \boldsymbol{F}\boldsymbol{x}_k + \boldsymbol{G}\boldsymbol{w}_k \tag{8}$$

where $\boldsymbol{F}$ and $\boldsymbol{G}$ are $r(\beta+1) \times r(\beta+1)$ and $r(\beta+1) \times (m+1)(\beta+1)$ matrices respectively, and $\boldsymbol{w}_k$ is a $(\beta+1)(m+1) \times 1$ zero mean white Gaussian vector process with the covariance matrix defined as $E\{w_k w_l\} = \boldsymbol{Q}\delta_{kl}$.

Also, by defining the $r(\beta+1) \times 1$ vector $\boldsymbol{H}_k$ as

$$\boldsymbol{H}_k = (b_k, b_{k-1}, b_{k-2}, \ldots, b_{k-\beta}, 0, \ldots, 0) \tag{9}$$

where $(r-1) \times (\beta+1)$ zeros are inserted after $b_{k-\beta}$, we can write

$$z_k = \boldsymbol{H}_k \boldsymbol{x}_k + n_k \tag{10}$$

and the covariance of the additive Gaussian noise is $E\{n_k n_l^T\} = N_o \delta_{kl}$.

Equations (8) and (10) describe a linear time varying system as shown in Fig2, where $\boldsymbol{x}_k$ is the state vector of this system and $\boldsymbol{F}$ is the state transition matrix. $\boldsymbol{H}_k$ is the measurement matrix and the received signal z_k can be assumed to be a noisy measurement of the state of the system. In the following section we will consider the multiplicative distortion effect of Rayleigh fading channels

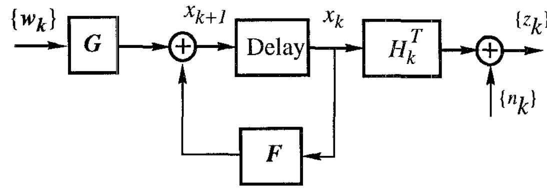

Fig. 2: Linear time varying model of signal transmission over a Rayleigh fading channel.

and based on that we will build another model for the channel. Then we will define the parameters of the time varying linear system of Fig. 2 according to our new model.

3. THE CHANNEL MODEL

The baseband impulse response of a two-ray fading channel can be written as:

$$c(t,u) = \alpha_o(t)\,\delta(t-u) + \alpha_1(t)\,\delta(t-u-\tau) \tag{11}$$

where α_0 and α_1 are Gaussian complex random coefficients, and their real and imaginary parts are independent Gaussian processes with the same mean and variances. Simulation of the fading spectrum appropriate to mobile radio is obtained by properly shaping the spectrum of these Gaussian processes, i.e. by choosing an appropriate characteristic for the two fading filters in Fig. 3.

It is important to notice that although the spectrum of a Gaussian process is affected by filtering, the PDF is not, so the process at the output of the fading filter remains Gaussian. The required spectrum for the fading filter for isotropic scattering and an omnidirectional antenna is represented by [8] as

$$A_o(f) = \begin{cases} \dfrac{E_o}{4\pi f_m} \dfrac{1}{\sqrt{1 - \left(\dfrac{f}{f_m}\right)^2}} & |f| \le f_m \\ 0 & elsewhere \end{cases} \tag{12}$$

It is too difficult to design a filter that truly follows this shape, so an approximation has to be sought [8].

The fading filter can be approximated by a third order filter [9] and the transfer function in the z domain can be written as

$$P(z) = \frac{D}{1 - Az^{-1} - Bz^{-2} - Cz^{-3}} \tag{13}$$

Consider the channel as the combination of a raised-cosine filter and a time variant fading channel, as shown in Fig. 4(a).

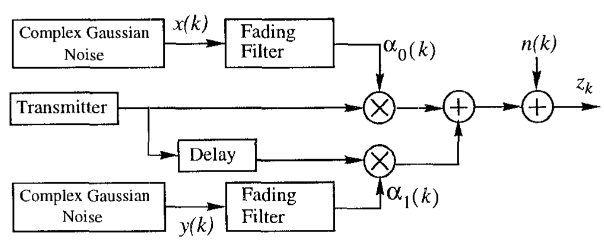

Fig. 3: The fading channel model

The response of the fading channel at time n to an impulse applied at time k is shown in Fig. 4(b) and can be expressed as

$$c(k, n-k) = \alpha_o(k)\,\delta(n-k) + \alpha_1(k)\,\delta(n-k-\tau) \tag{14}$$

The response of this time variant system to an arbitrary input $u(n)$ can be written as

$$o(n) = \sum_m c(m, n-m)\,u(m) \tag{15}$$

For the cascade of two systems we want to find the response to $\delta(n-k)$, or $h_{k,n-k}$. This is equivalent to finding the response of the fading channel to the input signal $f(n-k)$ and from (15) we have

$$h_{k,n-k} = \sum_m c(m, n-m)\,f(m-k) \tag{16}$$

Using (14), $h_{k,n-k}$ can be expressed as

$$= \sum_m [\alpha_o(m)\,\delta(n-m) + \alpha_1(m)\,\delta(n-m-\tau)]\,f(m-k) \tag{17}$$

$$= \alpha_o(n) f(n-k) + \alpha_1(n-\tau) f(n-k-\tau) \tag{18}$$

and if we define $i=n-k$, (18) becomes

$$h_{k,i} = \alpha_o(k+i) f(i) + \alpha_1(k+i-\tau) f(i-\tau) \tag{19}$$

In (4) the impulse response is defined as the vector $\boldsymbol{h}_k$ with components $h_{k,i}$, and (19) defines the ith component of the vector $\boldsymbol{h}_k$. On the other hand, from Fig. 3 we can see that $\alpha_o(k+i)$ and $\alpha_1(k+i-\tau)$ are outputs of the fading filter and can be written as

$$\alpha_o(k+i) = x(k+i) * p(k) \tag{20}$$

and

$$\alpha_1(k+i-\tau) = y(k+i-\tau) * p(k) \tag{21}$$

where $p(k)$ is the impulse response of the fading filter. Hence (19) becomes

$$h_{k,i} = [x(k+i) * p(k)]f_i + [y(k+i-\tau) * p(k)]f_{i-\tau} \tag{22}$$

or

$$h_{k,i} = [f_i x(k+i) + f_{i-\tau} y(k+i-\tau)] * p(k) \tag{23}$$

Equation (23) suggests that the impulse response of the combination of $f(t)$, and the fading channel, can be obtained at the output of the fading filter, if the input is the Gaussian noise process $w_{k,i}$ as shown in Fig. 5.

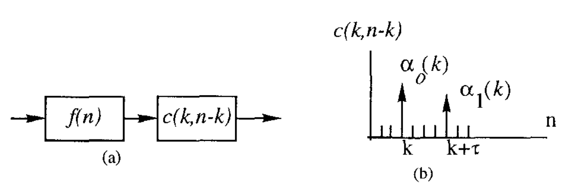

Fig. 4: (a) The combination of raised-cosine filter and fading channel, (b) Time variant impulse response of the fading channel.

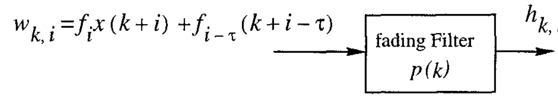

Fig. 5: Illustration of the channel impulse response as the output of the fading filter.

Given the transfer function of the fading filter $P(z)$ as in (13), one can obtain the ARMA representation of the channel impulse response as

$$h_{k,i} = Ah_{k-1,i} + Bh_{k-2,i} + Ch_{k-3,i} + Dw_{k,i} \tag{24}$$

and if we write this equation for different values of i the matrix form of (6) will become

$$\boldsymbol{h}_k = A\boldsymbol{I}\boldsymbol{h}_{k-1} + B\boldsymbol{I}\boldsymbol{h}_{k-2} + C\boldsymbol{I}\boldsymbol{h}_{k-3} + D\boldsymbol{I}\boldsymbol{w}_k \tag{25}$$

From (25) one can easily find the matrices $\boldsymbol{F}$ and $\boldsymbol{G}$ and (8) becomes

$$\boldsymbol{x}_{k+1} = \begin{bmatrix} A\boldsymbol{I} & B\boldsymbol{I} & C\boldsymbol{I} \\ \boldsymbol{I} & 0 & 0 \\ 0 & \boldsymbol{I} & 0 \end{bmatrix} \boldsymbol{x}_k + \begin{bmatrix} D\boldsymbol{I} \\ 0 \\ 0 \end{bmatrix} \boldsymbol{w}_k \tag{26}$$

where $\boldsymbol{I}$ is a $(\beta+1)\times(\beta+1)$ unit matrix.

$\boldsymbol{H}_k$ is another parameter of the linear system of Fig. 2 and is defined in (9). This vector is different for each hypothesis in the receiver and depends on the hypothesized transmitted signal sequence.

As mentioned before, the covariance matrix of the Gaussian noise process $w_{k,i}$ is $E\{\boldsymbol{w}_k \boldsymbol{w}_l\} = \boldsymbol{Q}\delta_{kl}$ and the matrix $\boldsymbol{Q}$ can be obtained using the definition

$$w_{k,i} = f_i x(k+i) + f_{i-\tau} y(k+i-\tau) \tag{27}$$

The element on the ith row and the jth column of $\boldsymbol{Q}$ is

$$q_{ij} = E\{w_{k,i} w_{k,j}\} \tag{28}$$

or

$$= E\{[f_i x(k+i) + f_{i-\tau} y(k+i-\tau)] \times [f_j x(k+j) + f_{j-\tau} y(k+j-\tau)]\}$$

x and y are white processes with variances σ_x^2 and σ_y^2,therefore q_{ij} is zero for $i \neq j$ and for the diagonal elements of $\boldsymbol{Q}$ we obtain

$$q_{ii} = f_i^2 \sigma_x^2 + f_{i-\tau}^2 \sigma_y^2 \tag{29}$$

Having defined the parameters of the linear system of Fig. 2, we are ready to employ an estimation method for estimating the impulse response of the channel.

4. Estimation Methods

A. The Kalman Filter

The Kalman filter is an optimal linear minimum variance estimator. The equations (8) and (10) form a Kalman filtering problem; and the following solution is well known for the Kalman Filter:

Measurement Update Equations:

$$\hat{x}_{k|k} = \hat{x}_k + K_k(z_k - H_k\hat{x}_k) \quad (30)$$

$$K_k = P_k H_k^T R_k^{-1} \quad (31)$$

$$R_k = H_k P_k H_k^T + N_o \quad (32)$$

$$P_{k|k} = P_k - K_k H_k P_k \quad (33)$$

Time Update Equations:

$$\hat{x}_{k+1} = F\hat{x}_{k|k} \quad (34)$$

$$P_{k+1} = FP_{k|k}F^T + GQG^T \quad (35)$$

$\hat{x}_k$ is the estimate of x_k and P_k is the error covariance matrix of state estimates. By the measurement update equations, the Kalman filter estimates the state vector or the CIR based on a noisy measurement. Then, using time update equations, the filter updates its estimate according to its knowledge of the linear system parameters.

B. The RLS Algorithm (kalman Algorithm)

The RLS algorithm is a least squares method to minimize a cost function. The RLS algorithm with exponential weighting uses the cost function $\xi(i)$ given by

$$\xi(i) = \sum_{k=1}^{i} \lambda^{i-k} |z_k - H_k\hat{x}_k|^2 \quad (36)$$

where λ is a forgetting factor and the cost function is minimized by the following algorithm

$$\hat{x}_{k+1} = \hat{x}_k + K_k(z_k - H_k\hat{x}_k) \quad (37)$$

$$K_k = P_k H_k^T R_k^{-1} \quad (38)$$

$$R_k = H_k P_k H_k^T + \lambda \quad (39)$$

$$P_{k+1} = \lambda^{-1}(P_k - K_k H_k P_k) \quad (40)$$

We can observe that the RLS algorithm is basically the same as *the measurement update* equations of the Kalman filter. By these equations, the estimator uses the information of the received signal to update its state estimates, while in *the time update* equations the Kalman filter uses its knowledge about the linear system and updates the estimated values at the next discrete time step according to this information. Hence, when we do not have enough information about the channel system, the RLS algorithm is a good choice and when the channel parameters are known we can implement the Kalman filter which is the optimal estimator.

5. Joint Data and Channel Estimation

MLSE is implemented via the Viterbi algorithm for communication over a known channel, and in the case of an unknown channel, an estimate of the channel impulse response is required at the receiver. Also, both the Kalman filter and the RLS algorithm require the vector H_k, which depends on the transmitted data, however, the transmitted data is not available at the receiver.

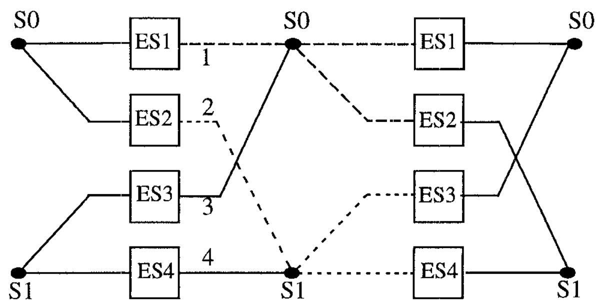

Fig. 6: The generalized Viterbi algorithm with channel estimators on trellis branches.

Channel estimation is usually performed by using the LMS or RLS algorithms in a decision directed method. In this method the detected data is used for channel estimation and it leads to an inherent decision delay which is not desired. To avoid the decision delay the method of joint data and channel estimation has been proposed by some authors[2][7]. In this method, there is a channel estimate for every possible sequence, and to overcome the problem of uncertainty in H_k we build Kalman filters for all of the possible hypothesized H_k vectors. However, the direct implementation of this exhaustive method is too difficult, as the required computation grows exponentially with the sequence length. The implementation can be made possible by using a generalized Viterbi algorithm, where each surviving path keeps and updates its own channel estimate.

Fig. 6 shows a simple trellis diagram with the channel estimators on each branch. Each estimator considers a hypothesized transmitted sequence and estimates the CIR based on this hypothesis. Then, after computing the branch metrics and choosing the survivor path, the states of the estimators on each surviving path will be passed to the estimators of the next stage. In Fig. 6, assume that branches numbered 1 and 2 are the surviving paths to S0 and S1. Hence, the current state of the estimator ES1 determines the initial conditions of estimators ES1 and ES2 in the next stage; and also, the initial conditions of ES3 and ES4 will be determined by the current state of ES2. Each estimator will use it's own hypothesis and the information of the surviving path to build the vector H_k. By this method, it is guaranteed that we are using the data sequence of the shortest path for the channel estimation along the same path, which is obviously the best available information at the receiver. This method also eliminates the problem of decision delay.

Using the channel model of section 3 makes it possible to employ the Kalman estimator. The parameters of the channel fading IIR filter in equation (13) can be found according to the maximum Doppler frequency shift, and the time update equations of the Kalman filter can be implemented using these parameters.

In the next section, we present the simulation results where the effect of using the Kalman filter on lowering the bit error rate is studied.

6. Simulation Results

In the computer simulations, the modulation scheme employed is differentially coherent QPSK, with a symbol rate of 25 ksymbol/s. As in the IS-54 standard, the data sequence is arranged into 162 symbol frames. The first 14 symbols of each

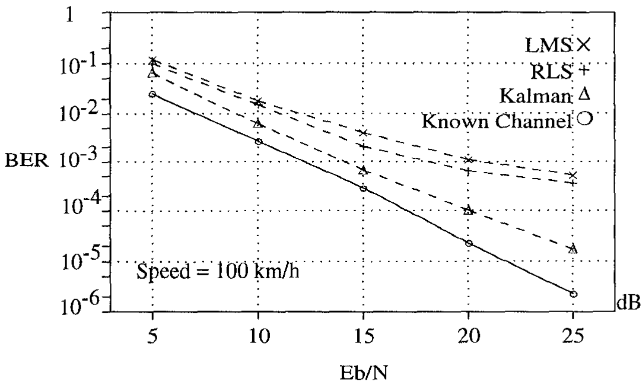

Fig. 7: Simulation results with different estimation methods.

frame is a training preamble sequence to help the adaptation of the channel estimator. The transmitting and receiving filters are FIR filters with a square-root-raised cosine frequency response with excess bandwidth of 25%. The receiver takes 3 samples per symbol interval and the complex samples are processed by the digital processor to detect the transmitted data. The fading channel is simulated as a symbol-spaced two-path model with time varying complex coefficients. The two fading paths are independent with equal strength, and are implemented as shown in the model of Fig. 3.

The total length of the channel impulse response is 2 symbol intervals and there are four possible states in the trellis diagram. After each state in the trellis there are four possible states in the next stage. In some methods [7], when several paths enter one state, K of them with the lowest accumulated least squares error are retained and the others are discarded. This method leads to better detection results at the expense of more computation. In our simulations we choose K=1 and we focus our attention on the comparison of different methods. However, implementing the simulation for bigger K is always possible with any of the estimation methods.

Fig. 7 shows the simulation results for a vehicle speed of 100 km/h. The BER performance of different estimators are compared here. In each simulation different channel estimators are used to estimate the channel impulse response on every received sample. The performance results of the RLS algorithm is superior to that of LMS algorithm by about 3 dB at a BER=10^{-3}. Choosing the Kalman estimator provides 7 dB improvement in performance over the LMS algorithm at the same BER.

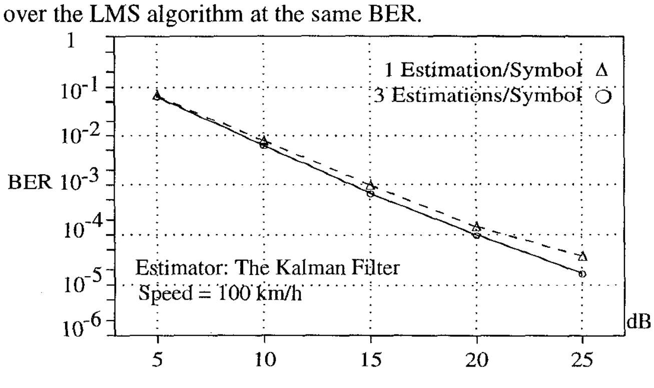

Fig. 8: The result of changing the estimation rate for the Kalman estimator.

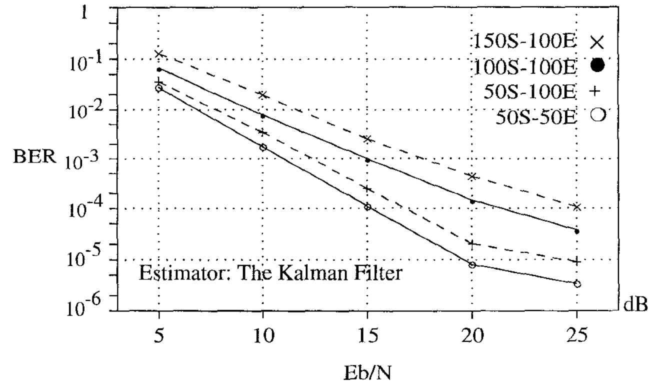

Fig. 9: The effect of error in estimation of Doppler frequency shift, using the Kalman Filter.

The last curve is for the case of data detection over a known channel. In this case we have assumed that the exact channel impulse response is always present at the receiver and there is no need to estimate it. Of course this situation is not possible in a practical implementation, and this can be looked at as an error free estimation method giving a lower BER bound for comparison. The performance of the Kalman filter is about 2 dB poorer than the best possible results obtained with a known channel at a BER=10^{-3}. By considering a larger value for K it is possible to attain better performance and reduce this gap.

When the channel impulse response does not change very rapidly, the channel estimation can be performed at a lower rate. This leads to less computation at the receiver. Fig. 8 compares the results for the Kalman estimator for the situation of one channel estimation every symbol interval and the situation of one channel estimation every sample interval which is 3 times longer. As we can see there is only a difference of about 1.5dB at a BER=10^{-4} between the two methods, which in some cases, might be tolerated to reduce the complexity of the receiver.

As mentioned before, to employ the Kalman filter estimator the receiver computes the matrices $\boldsymbol{F}$ and $\boldsymbol{G}$ based on its assumption about the Doppler frequency shift. In Fig. 9 we can observe the effect of error in the estimation of the Doppler frequency shift. The curve labeled 100S-100E is for the normal case where the actual speed of the vehicle is 100 km/h and it is correctly assumed as 100 km/h in the receiver. The curves 150S-100E and 50S-100E show the situation where the actual speed is 150 and 50 km/h, respectively, but in both cases the speed is assumed to be 100 km/h at the receiver. And finally for the 50S-50E curve the receiver assumes the correct speed for a vehicle with the speed of 50 km/h.

In Fig. 9 the dashed lines show the situation when the estimation of the vehicle speed is in error by 50 km/h and in both cases the performance is about 2 to 4 dB poorer than the case where we assume the correct speed for the vehicle. It can be easily observed that we can always attain better results than what we are expecting by overestimating the speed. By accepting a reasonable margin in BER performance, one may assign a limited number of speeds and switch from one preselected speed threshold to another when the vehicle speed changes.

In the RLS algorithm the overall BER performance depends on the chosen value for the forgetting factor, λ. Fig. 10 shows the BER curves for different values of λ. It can be seen that for small

Eb/N, bigger values of λ yield better results, while for high Eb/N values, λ should be smaller.

The RLS algorithm minimizes the average weighted squared error of (36), over an interval which is determined by λ. The above consequence means that in poor Eb/N conditions the estimator should consider a larger interval to minimize the cost function, while for high Eb/N values minimization over smaller intervals yields better performance.

From the above results, the superiority of the Kalman filter is clearly evident. The Kalman filter shows the best tracking performance for rapidly changing time-variant channels, followed by the RLS algorithm as the next best choice as a good estimator with fast tracking. However, in spite of their superior tracking performance, the Kalman filter and the RLS algorithm have two disadvantages. One is the sensitivity of these recursive algorithms to round off noise. This may cause numerical instabilities such that algorithm may diverge due to this round off noise.

There are different implementation methods for the Kalman filter [10] and studies show that some implementations are more robust against round off errors. The "square root" filter implementations are frequently employed to maintain the required robustness against error propagation in recursive algorithms. For examples of Kalman filter implementations the reader is referred to [11-14].

The second problem with the Kalman filter and the RLS method is that these algorithms are computationally intensive. The complexity of the Kalman filter is proportional to N^3, and for the RLS algorithm it is proportional to N^2, where N is the number of states. The heavy computational burden originates from the iterative processing of the matrix operations.

The suitability of systolic arrays for matrix computations has prompted their application to the Kalman filter. In the literature, there have been several VLSI systolic array designs for the Kalman filter [10], and alternative systolic Kalman filters exhibit different size, speed and efficiency trade-offs. Using systolic architectures one can speed up the matrix computations and make the algorithm suitable for real time applications.

7. Conclusions

In this paper we proposed a sequence estimation technique using joint data and channel estimation over the frequency selective Rayleigh fading channel. In this method a generalized Viterbi decoder and different estimators were employed to estimate the channel impulse response and it was shown that using the Kalman filter leads to the best BER performance.

Based on the fading properties and the Doppler frequency shift an ARMA representation for the channel impulse response was derived in section 3. This channel model makes it possible to implement the Kalman filter. It was important to have a correct estimation of the Doppler frequency shift at the receiver. By considering the effects of error in speed estimation, we concluded that it is always better to overestimate the vehicle speed. In the RLS algorithm choosing a proper value for λ was considered, and square root filtering, implemented in the form of VLSI systolic architectures was proposed to combat the complexity problems of the Kalman filter and the RLS algorithm.

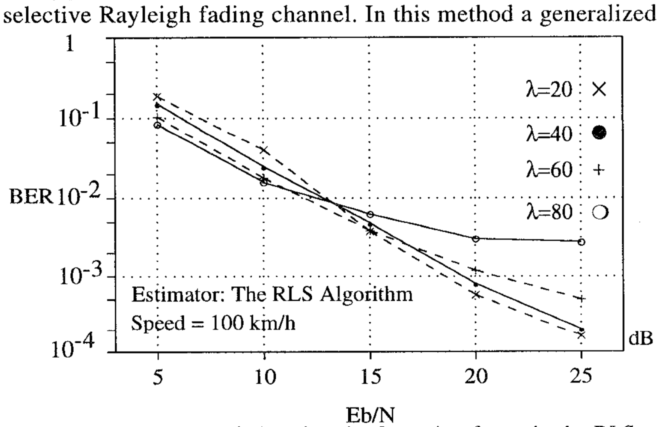

Fig. 10: The effects of changing the forgetting factor in the RLS algorithm on the overall BER performance.

Rererences

[1] Dai, Q. and Shwedyk, E., "Detection of bandlimited signals over frequency selective Rayleigh Fading channels" *IEEE Trans on Communications*, vol. 42, pp. 941-950, Feb/ Mar/Apr 1994.

[2] K. Fukawa, H. Suzuki, "Adaptive equalization with RLS-MLSE for frequency-selective fast fading mobile radio channels," *Globecom'91*, pp. 16.6.1-16.6.5, 1991.

[3] Iltis, R. A., "A Bayesian maximum-likelihood sequence estimation algorithm for a priori unknown channels and symbol timing," *IEEE Journal of Selected Areas in Communications*, vol. 10, pp. 579-588, April 1992.

[4] H. Kubo, K. Murakami, T. Fujino,"An adaptive Maximum-likelihood sequence estimator for fast time-varying intersymbol interference channels," *IEEE Transactions on Communications*, Vol. 42, pp. 1872-1880, Feb/Mar/Apr 1994.

[5] S.U.H. Qureshi, "An adaptive decision-feedback receiver using maximum-likelihood sequence estimation," *Proceeding of IEEE International Conference on Communication.*, pp. 14.10-14.16, 1973.

[6] W.U. Lee, F.S. Hill, Jr.,"A maximum-likelihood sequence estimator with decision-feedback equalization," *IEEE Transaction on Communication*, vol. COM-25, pp. 971-979, Sept. 1977.

[7] J. Lin, F. Ling, J. G. Proakis, "Joint data and channel estimation for TDMA mobile channels," *International Journal of Wireless Information Networks*, Vol. 1, No. 4, pp. 229-238, 1994.

[8] J.D. Parsons, "The mobile radio propagation channel," *Pentech Press*, 1992.

[9] A. Gaston, W. H. Chriss, E. H. Walker, "A multipath fading simulator for radio," *IEEE Transaction on Vehicular Technology*, vol. 22, pp. 241-244, 1973.

[10] Gaston, F.M.F. and Irwin, G.W., "Systolic Kalman filtering: an overview," *IEE proceedings*, vol. 137 Pt. D, No. 4, pp. 235-244, July 1990.

[11] Rao, P. and Bayoumi, M. A., "An efficient VLSI implementation of real-time Kalman fitter," *IEEE International Symposium on Circuit and Systems*, vol. 3, pp. 2353-6, 1990.

[12] Rao, P. and Bayoumi, M. A., "An algorithm specific VLSI parallel architecture for Kalman filter," *VLSI Signal Processing IV*, IEEE Press, pp. 264-273, 1991.

[13] Jover, J. M. and Kailath, T., "A parallel architecture for Kalman filter measurement update and parameter estimation," *Automatica*, vol. 22, No. 1, pp. 43-57, 1986.

[14] Bayoumi, M. and Rao, P., Alhalabi B., "VLSI parallel architecture for Kalman filter an algorithm specific approach," *Journal of VLSI Signal Processing*, 4, pp. 147-163, Kluwer Academic Publishers, 1992.