

Measuring of channel coefficient using “KALMAN filter”

Ms. Ruchi Dahiya¹, Mrs. Meenu Manchanda², Mr. Manjeet³

¹M.Tech. Scholar, Vaish College Of Engineering
 Rohtak, Haryana, India
 ruchisingh96@yahoo.com

²Asst. Professor, Vaish College Of Engineering
 Rohtak, Haryana, India
 meenumanchanda73@gmail.com

³ M.Tech. Scholar, Ambedkar Institute of Technology
 New Delhi, India
 manjeetchhilar@gmail.com

Abstract

In this paper, the channel is estimated by using kalman filter. The channel is time varying modeled as a low-Pass tapped delay line filter that is work as the FIR filter with time varying Coefficients. Here Kalman filter technique is used to estimate the time varying coefficient of the channel.

Keywords: Time varying channel, channel estimation, Kalman filter.

1. Introduction

Adaptive filter consider various type of filter like wiener filter, Kalman filter. Kalman filter has various advantages from others filter. The main feature is Kalman filter is that its mathematical formulation is described in terms of state space concept. Another advantage is that its solution is computed recursively, applying without modification to the stationary as well as non-stationary environments. Kalman filter is a liner, discrete time finite dimensional system endowed with a recursive structure that make a digital computer well studied for its implementation.

The main property of Kalman filter is that it is minimum mean square (variance) estimator of the state of the liner dynamical system, which follows from a stochastic state space model.

2. CHANNEL ESTIMATION

The estimator means filter. The filter is commonly used to a system that is designed to extract information about a prescribed quantity of interest from noisy data. The channel effects like a medium through which the signal is travel from sender to receiver. Channel estimation is to estimate the filter coefficient through received signal and other known information. The channel is act as a physical medium (free space, fiber etc.) between the transmitter & receive through which the signal travel. There are two

channel estimation methods are proposed. The Maximum Likelihood (ML) estimator is unbiased, but it is more sensitive to noise. The second channel estimation method, based on the minimization of the mean square error (MMSE). The signal received from the channel is suffer from phase-distortion, inter symbol interference and thermal noise. A channel model on the other hand can be thought of as a mathematical representation of the transfer characteristics of this physical medium. Most channel models are formulated by observing the characteristics of the received signals for each specific environment. Different mathematical models that explain the received signal are then fit over the accumulated data. The behavior of the received signal is used to model the given physical channel. The Channel estimation is defined as the process which characterizing the effect of the physical channel on the input sequence. The channel estimate, estimate of the impulse response of the system, if the channel assumed to be liner. It must be stressed once more that channel estimation is only a mathematical representation of what is truly happening. A good channel estimate is one where some sort of error minimization criteria is satisfied (e.g. Minimum Mean Square Error (MMSE)).

There is various reasons to estimate the channel. In which some are as that it allow the receiver calculate the impulse response. It is used to observe the behavior of the channel. Diversity techniques (for e.g. the IS-95 Rake receiver) utilize the channel estimate to implement a matched filter such that the receiver is optimally matched to the received signal instead of the transmitted one. One of the most important benefits of channel estimation is that it allows the implementation of coherent demodulation

3. PROBLEM FORMULATION

The tap delay line model requires that the No. of taps are $T_M W + 1$. Where T_M is delay spread and W is the information bandwidth. Secondly it requires Tap spacing is $1/W$. And it also requires Tap gain function are discrete time complex Gaussian processes with variances. The low pass tap delay model act as a FIR (finite Impulse response) with their time varying coefficient.

A low-pass tapped delay line model of the time varying channel is really nothing more than an finite impulse response (FIR) filter with time varying coefficients. The input-output description of the FIR filter with time varying coefficients is

$$s[n] = \sum_{k=0}^{q-1} h_n[k] x[n-k]$$

Where $h_n[k]$ are the time varying coefficients of the channel. On the basis of corrupted output of the channel we have to estimate the $h_n[k]$.

$$y[n] = s[n] + w[n]$$

$$s[n] + w[n] = \sum_{k=0}^{q-1} h_n[k] x[n-k] + w[n]$$

Where $w[n]$ is assumed to be white Gaussian noise (WGN) with variance σ^2 .

Assume that the weights will not change rapidly from sample to sample. For Example, a slow-fading channel. Statistically, we may interpret the slow variation as a high degree of correlation between samples of the same tap weight. This observation leads us to model the tap weights as random variables whose time variation is described by a Gauss-Markov model. The use of such a signal model allows us to fix the correlation between the successive values of a given tap weight in time. Hence, we suppose the state vector is

$$h[n] = Ah[n-1] + u[n]$$

where $h[n] = [h_n[0], h_n[1], \dots, h_n[q-1]]^T$,

A is a known $q \times q$ matrix,

$u[n]$ is the vector WGN with covariance matrix Q .

A standard assumption that is made to simplify the modeling is that of the uncorrelated scattering [2]. We assume that the tap weights are uncorrelated with each other and hence independent due to jointly Gaussian assumption. As a result, we can let A, Q and C_n , the covariance matrix of $h[-1]$ be diagonal matrices. The vector Gauss-Markov model then becomes q independent scalar models. The measurement model is, from (2)

$$y[n] = [x[n], x[n-1], \dots, x[n-q+1]]h[n] + w[n] \quad (4)$$

let $x^T[n] = [x[n], x[n-1], \dots, x[n-q+1]]$. Equation (4) is equivalent to

$$y[n] = x^T[n]h[n] + w[n] \quad (5)$$

We can now form the minimum mean square error (MMSE) estimator for the tapped delay line weights recursively in time using the Kalman filter for this particular problem (vector state and scalar observations).

4. KALMAN FILTER

Kalman filter is a MMSE (minimum mean square error) estimator of a signal embedded in noise, where the signal is characterized by a dynamic or state model. If the signal and noise are jointly Gaussian, then the Kalman filter is an optimal MMSE estimator, and if not, it is the optimal LMMSE estimator. Equation (3) represents the vector state model and equation (5) is scalar observation or measurement equation. The Kalman filter equations for this problem are [4]:

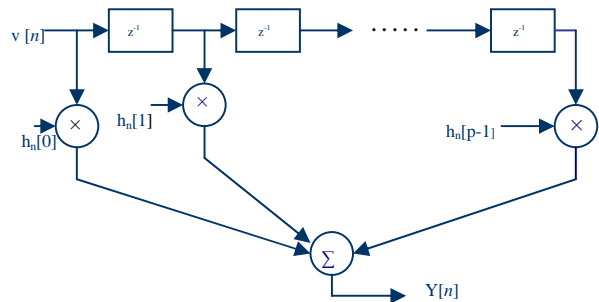


Fig.1 Channel true weights

Prediction:

$$\hat{h}[n|n-1] = A\hat{h}[n-1|n-1]$$

Minimum Prediction MSE matrix ($q \times q$):

$$M[n|n-1] = AM[n-1|n-1]A^T + Q$$

Kalman Gain:

$$K[n] = \frac{M[n|n-1]x[n]}{\sigma^2 + x^T[n]M[n|n-1]x[n]}$$

Correction:

$$\hat{h}[n|n] = \hat{h}[n|n-1] + K[n](y[n] - x^T[n]\hat{h}[n|n-1])$$

Minimum MSE:

$$M[n|n] = (I - K[n]x^T[n])M[n|n-1]$$

Initialization matrices are:

$$\hat{h}[-1 | -1] = \mu_h$$

$$M[-1 | -1] = C_h$$

5. SIMULATION AND RESULTS

Let the Kalman filter estimator have $q = 2$ weights.

Assume a state model with $A = \begin{bmatrix} 0.99 & 0 \\ 0 & .999 \end{bmatrix}$ and

$Q = \begin{bmatrix} 0.0001 & 0 \\ 0 & 0.0001 \end{bmatrix}$ True values of the weights are shown in Fig. 2, in which $h_n[0]$ is decaying to zero while $h_n[1]$ is fairly constant. This is because the mean of the weights will be zero in steady state. Due to the smaller value of $[A]_{11}$, $h_n[0]$ will decay more rapidly. Also, note that the eigen values of A are just the diagonal elements and they are less than 1 in magnitude. The o/p is determined from (1). When observation noise is added with $\sigma^2 = 0.1$, the channel output $y[n]$ is shown in Fig. 4. Let $\hat{h}[-1 -1] = \mu_h = 0$ and $M[-1 -1] = C_h = 100I$, which were chosen to reflect little knowledge about the initial state. In the theoretical development of the Kalman filter the initial state estimate is given by the mean of $s[-1]$.

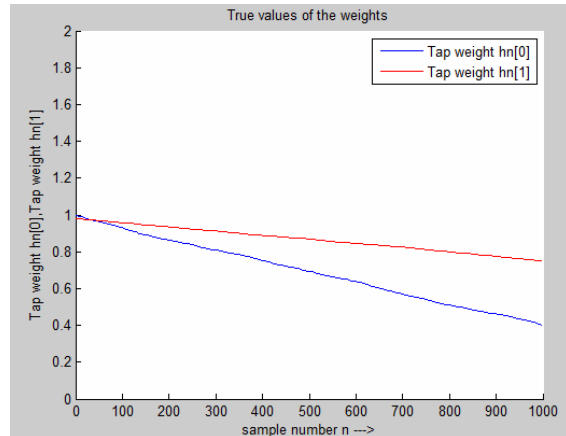


Fig.2 True values of the weights

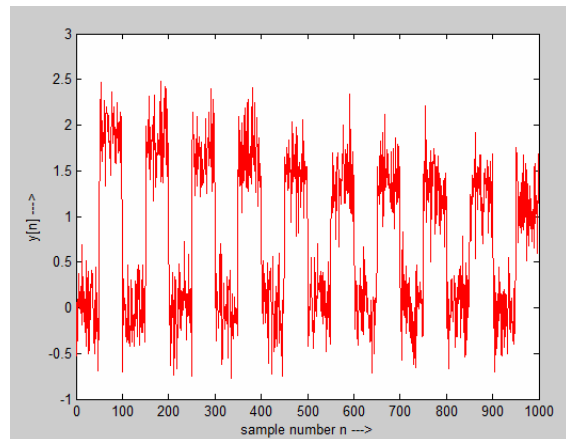


Fig.4 channel output y[n]

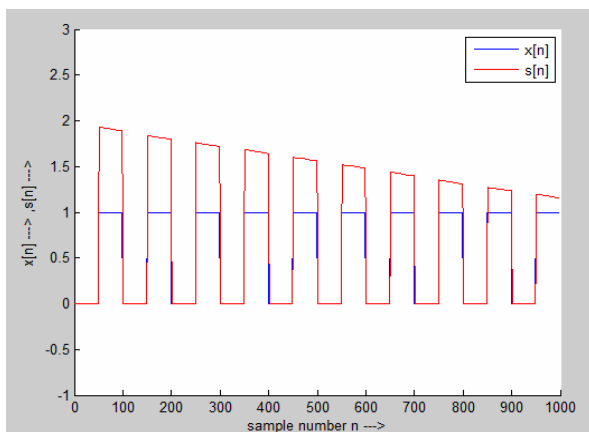


Fig 3 input sequence

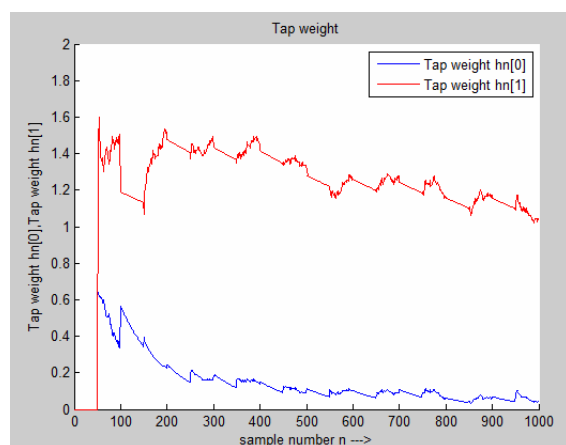


Fig. 5 estimated Tap weight

In practice this is seldom known, so that we usually just choose an arbitrary initial state estimate with a large initial MSE matrix to avoid “biasing” the Kalman filter towards that assumed state. The estimated tap weights are shown in Fig. 5. After an initial transient the Kalman filter “locks on” to the true weights and tracks them closely. The Kalman filter gains are shown in Fig. 6.

They appear to attain a periodic steady-state, although this behavior is different than the usual steady-state, since $x[n]$ varies with time and so true steady-state is never attained. Also, at times the gain is zero, as for example in $[K]_1 = k_1[n]$ for $0 \leq n \leq 4$. This is because at these times the input $x[n]$ is zero and thus the observation contain only noise. The Kalman filter ignores these data samples by forcing the gain to be zero. Finally, the minimum MSEs are shown in Fig. 7

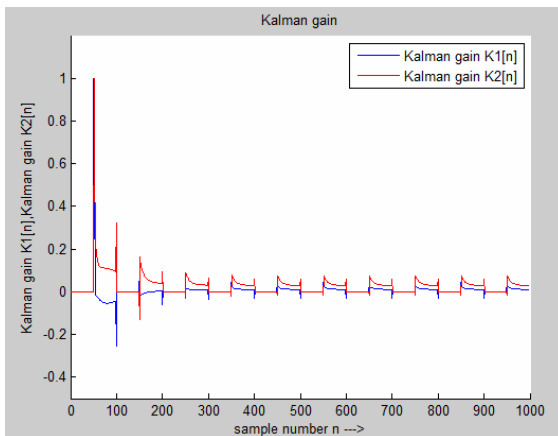


Fig.6 Kalman filter gain

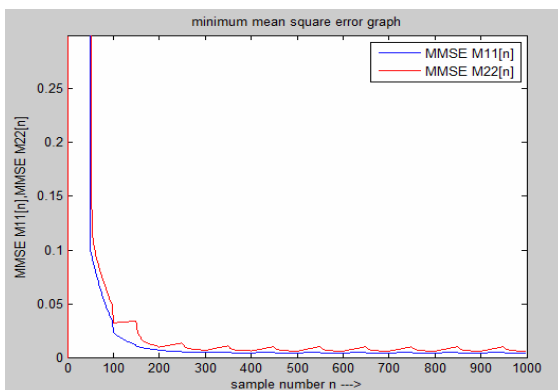


Fig.7 Minimum MMSE

In this paper, the channel is modeled as an FIR filter with time varying coefficients. The observation model is assumed to be Gauss-Markov for tap weights. Kalman filter is used to estimate the time varying coefficients of the channel

REFERENCES:

- [1] B. Sklar, Rayleigh fading channels in mobile digital communication systems, Part I: Characterization, IEEE Communications Magazine, 1997, vol. 35, no. 7, pages: 90 - 100.
- [2] H. L. Van Trees, Detection, Estimation, and modulation Theory III, John Wiley & Sons, Inc., New York, 1971.
- [3] R. E. Kalman, A New Approach to Linear filtering and prediction problems, Transactions of the ASME Journal of Basic Engineering, cat 82 (Series D), pages: 35 - 45, 1960
- [4] S. M. Kay, Fundamentals of statistical signal processing: estimation theory, PTR Prentice Hall, Englewood Cliffs, New Jersey 07632
- [5] Masoud Salehi & John G. Proakis, Communication Systems Engineering, 2nd Edition, Prentice Hall, 2002.

6. CONCLUSION