Robust Fading Channel Estimation under Parameter and Process Noise Uncertainty with Risk Sensitive Filter and Its comparison with CRLB

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Abstract: -As an alternative to Kalman filtering, a risk-sensitive filtering is proposed for a linear time-varying fading channel estimation problem and its robustness against the parameter and process noise uncertainty in the channel model is explored. The time-varying channel estimation problem is formulated as time varying Finite Impulse Response (FIR) filter with a known rectangular pulse at input and Gaussian noise corrupted signal at output. In time-varying FIR filter, estimation of time varying coefficients with uncertain condition is an important and critical task. In literature, Kalman filter (KF) based fading channel estimation approach has been studied and it has limitations that lead to inaccurate estimation when there is a high level of uncertainty in initial conditions and bias in system model and/or noise covariance. To overcome the above limitation, the risk sensitive filter (RSF) is proposed. In this work, bias in channel is considered to investigate the effect of risk/cost performance of channel estimation problems. The special feature of risk sensitive filter is it uses a risk factor/parameter in the exponential cost function, so that the probability density function of variable of interest to be estimated and to be reshaped with proper tuning of risk factor, thus robustness again uncertainty can be achieved. In this paper, with KF and RSF the robustness against uncertainty in channel model parameter and process noise covariance is presented. Numerical simulation result has been carried out and the Root Mean Square error (RMSE) with Monte Carlo runs is studied. In order to estimate the Channel parameter under uncertain conditions, the performance of risk sensitive filter is improved than the conventional Kalman filter. To investigate the theoretical performance, Cramer-Rao Lower Bound (CRLB) is applied and its channel estimation performance is compared with performance obtained by the filters. When uncertainty is present in parameter, the risk sensitive filter's performance is comparatively close to that of CRLB performance than the performance of Kalman Filter.

Keywords- Channel Estimation, Fading Channel, Time-varying Coefficients, Kalman Filter, Risk Sensitive Filter, Cramer-Rao Lower Bound,Uncertainty.

1 Introduction

The quality of communication highly depends on efficient and accurate retrieval of information that has been transmitted from one place to another through transmission channel, which is normally affected with noise. To qualitatively improve a communication system, knowledge of channel is required and it may be achieved with channel estimation. Therefore, channel estimation problem consequently is a main and important part in communication, for example [2-7, 12-14].

In the real-world communication systems, characteristic of channel is fading in nature and more research is focused on it, for example, [19] presents Rayleigh fading channel model for QPSK transmitted data,[3] discuss the fading channel estimation with cross coupled H_∞ filter for advanced modulation technique namely Orthogonal Frequency Division Multiplexing (OFDM)[14], CDMA[15] and TDMA[22]. In modelling of MIMO-OFDM system, fading parameter and time-varying channel coefficients are important components [5], [8]. In [11] received OFDM symbol in time domain at receiver is taped-delay AR model. In general, fading factor will be chosen as close to 1 in order to satisfy the assumption that channel impulse response does not change within one OFDM symbol duration and it has been demonstrated with the simulation, by taking its value ranging from 0.90 to 1 [12]. Here we considered general channel estimation problem without specifying particular modulation techniques in communication system. Therefore, OFDM is not presented in this work and for much more details reader can refer [3-14, 22].

If the assumption of fading factor is less than 1, the modelled fading channel will be slow fading channel as the coherence time is greater than the symbol time. On other hand, practically it is not feasible to maintain slow fading range due to various factors involved in channel modelling including modelling error and parameter uncertainty. In this worst case, fading factor in AR model of channel may be greater than 1 and it can be modelled as parameter uncertainty in general AR channel model.

This work initially focused on time varying coefficient estimation of fading-channel, which is simple well- known simple time-delay, discrete, Finite-Impulse Response (FIR) based AR model given in [1] using Kalman filter (KF) and Risk Sensitive filter (RSF) and secondly uncertainty is introduced in the same channel model. The considered uncertain channel model in state-space representation is as given in [2, 21] and this model may be referred as bias in model or inaccurate state model of system, channel of communication system.

In literature [1, 4], it is found that Kalman filter is one of the competitive tools used for linear channel estimation problems. The limitations of Kalman filter is addressed in [1-2, 9, 23-25]. The main limitation of KF on linear estimation problems is that if there is bias, in this work we call it uncertainty in the system modelling, the KF is not suitable to produce optimal estimation [2],[21]. To overcome this problem, a filter based on risk sensitive approach, which reshapes probability density function using a risk parameter, has been developed [2],[9],[24-27]. In [18], H_∞ filter is used for equalization of communication channels where channel model is linear time-invariant.

Based on the performance index with conditional density formulation for risk measurement, three forms of risk sensitive filter algorithms were derived and its comprehensive can be found by refereeing [2],[24-26], which are generally and slightly varied in propagating estimated state and estimated error covariance of filters. In this paper, pure Risk Sensitive Filter (RSF), which updates posterior state and posterior covariance recursively [26], is utilized to illustrate the robust channel parameter estimation. With Monte Carlo simulation runs, robust channel estimation performance of KF and RSF compared over its theoretical Cramer-Rao lower bound.

Rest of the paper is organized as follows: Section-2 discusses the generic communication system model to indicate that channel is a important component in digital communication system. Section-3 presents channel state-space model with and without uncertainty. State estimation algorithms; KF and RSF, and CRLB are implemented for Channel Estimation in section-4. Numerical simulation results are shown in section-5 and section-6 concludes the work.

2 Generic System

The general virtual communication system comprises various subsystems [17]. Channel is the heart of communication systems and high level model, block diagram, of a "generic" one-hop communication system is shown in Fig. 1.

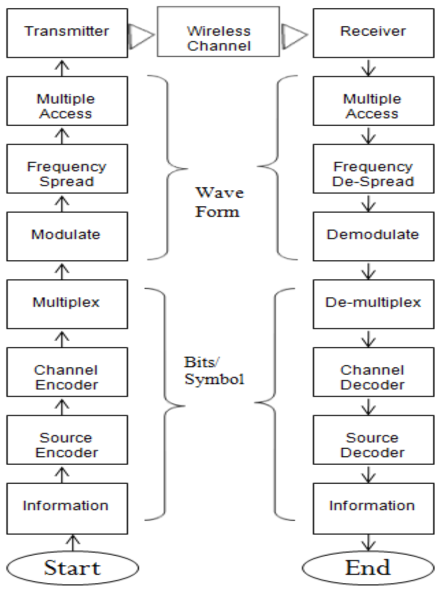

Fig-1 Block diagram of a "generic" one-hop communication system

It is clear from fig.1 that first few subsystems handle the information in bits/symbols and at some blocks close to channel the information processed by them are in waveform. Therefore, wave-form simulation is presented in this work as in [1]. In general, channels, transmission mediums, are characterized as linear-time varying systems unless otherwise specified.

It is assumed that transmission medium is just like a linear Filter that is modelled as Finite Impulse Response filter. Furthermore to study the characteristics of linear system, it is required to analyze the input and output of system.

3 Time-Varying Channel Model

This section describes the time-varying fading channel and its characteristics in detail. For more details refer [17, 28]. It is started with basic parameters, which are used to describe the characteristics of fading channel and ended with auto-recursive and its equivalent state-space model. Besides channel model with uncertainty is explored before applying estimation algorithms.

In general, the transmitted signal from base station reaches the receiver over different paths through channel known as multipath channel and it may have different attenuations, due to atmospheric scattering, refraction or reflection and some other objects fall on its way. A simple multipath (path 1 and path 2) scenario is shown in Fig.2 (courtesy: [17]).

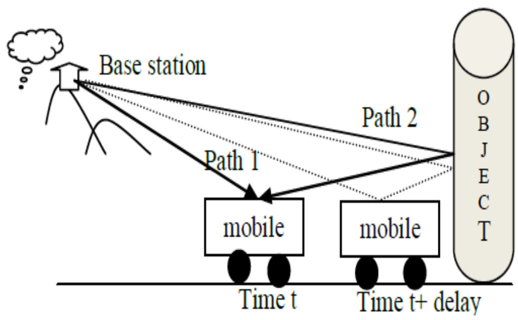

Fig.2 Multipath fading scenario

To characterize signal, propagate over multipath with uncorrelated time delay channel, in time and frequency domain a spread function is defined as

$$S(\tau,\lambda) = \int_{-\infty}^{\infty} R_h(\tau,\Delta t) e^{-j2\pi\lambda\Delta t} d\Delta t \quad (1)$$

Where $R_h(\tau,\Delta t)$ is autocorrelation function of multipath channel and it is written as

$$R_h(\tau,\Delta t) = E\{h^*[\tau,t]h[\tau,t+\Delta t]\} \quad (2)$$

τ is delay and λ is Doppler frequency. The delay-power profile is also called multipath intensity profile defined as

$$p(\tau) = R_h(\tau,0) = E\{h[\tau,t]^2\} \quad (3)$$

and it can be related with spread function as

$$p(\tau) = R_h(\tau,0) = \int_{-\infty}^{\infty} S(\tau,\lambda) d\lambda \,. \quad (4)$$

Doppler power spectrum of multipath fading channel is defined as

$$S(\lambda) = \int_{-\infty}^{\infty} S(\tau,\lambda) d\tau \quad (5)$$

The characteristic of multipath fading channel can be studied from equations (1)-(5). Multipath spread T_m of channel is the delay power spectrum from eqn. (4) is nonzero and similarly, non-zero value of Doppler power spectrum evaluated from eqn. (5) is Doppler spread B_d of channel.

The channel coherence time T_{coh} is defined as

$$T_{coh} = \frac{1}{B_d} \quad (6)$$

and channel coherence time is defined as

$$B_{coh} = \frac{1}{T_m} \quad (7)$$

Based on bandwidth W of transmitted signal $v[n]$ over channel and coherent bandwidth B_{coh}, fading is classified as frequency-selective ($W > B_{coh}$) and non-frequency selective $W \ll B_{coh}$ fading channel. This work is focused on frequency-selective fading channel. If $W \gg B_{coh}$, Channel impulse response components can be separated by delay at least *(1/W)* and it may be written as:

$$h[n] = \sum_{k=0}^{p-1} h_k[n]\delta(\tau - k/W) \quad (8)$$

This impulse response model is convenient to write as tapped delay line model.

3.1 Tapped delay line channel Model

A multiplicative channel model with an additive Gaussian white noise (AGWN) model is used; sometimes it is also referred as Gauss-Markov process.

$$y[n] = \textstyle\sum_{k=0}^{p-1} h_n\,[k]v[n-k] \quad (9)$$

where $v[n]$ is delay transmitted signal over channel. The function $y[n]$, and eqn.(1) is just same as Finite Impulse Response (FIR) filter which has time-varying coefficients. In real world scenario there are many factors, as disturbance, affect the medium, which leads to model the system with additive noise and as a result the system model becomes

$$x[n] = \sum_{k=0}^{p-1} h_n[k]v[n-k] + w[n] \quad (10)$$

To design effective communication, it is necessary to have good knowledge about these coefficients. Indeed optimal estimation technique is required to estimate these coefficients. There are too many parameters to estimate in eqn. (9). As observation samples are corrupted with noise, weights of samples will rapidly change from one to others. The weighted taped channel is modelled as Gauss-Markov model. The Gauss-Markov model is used to fix the correlation between successive values of given taped weight in time.

In channel estimation, the state vector is given as

$$h[n] = Ah[n-1] + u[n] \quad (11)$$

where,

$h[n] = \begin{bmatrix} h_n[0] \\ h_n[1] \\ \vdots \\ h_n[p-1] \end{bmatrix}$, A is a $p \times p$ matrix and

$u[n]$ is an AWGN with zero mean and variance Q.

A standard assumption made that tap weights are Gaussian and uncorrelated with each other.

Measurement/observation model is written by rearranging equ.(11)

$$x[n] = [v[n] \quad v[n-1] \quad v[n-2] \cdots \cdots v[n-p+1]]\, h[n] + w[n]$$

it can be expressed as

$$x[n] = V[n]^T h[n] + w[n] \quad (12)$$

where $[n]$, is Gaussian white noise with variance $R = \sigma^2$ and $v[n]$ is known as sequence, which acts as input to the channel.

3.2 Tapped delay line channel Model with uncertainty in parameter

In a circumstance, when there is uncertainty in the channel state vector, (11) may be written as

$$h[n] = Ah[n-1] + \Delta A + u[n] \quad (13)$$

Where, ΔA is a constant which arises due to channel phase rotation during coding and it is considered a parameter modelling uncertainty in matrix A. This model is similar to the case of random walk process described in [7] and in state-space domain the model eqn. (13) appears in the similar form as given in [2].

3.3 Tapped delay line channel Model with uncertainty in Process noise Variance

It is assumed that the noise variance in channel model varied from its actual value, therefore the process noise variance Q of u[n] may be written as

$$Q = Qfactor * Q$$

As the value of Q factor is not known in advance or exactly it is common that filter would not have knowledge of this change. So filter implementation is taking the Q factor into account. This would affect the cost function of filter while minimizing the estimated variables of interest. In this work, channel parameters are the variables of interest.

4 Channel Estimation Algorithms

To estimate channel coefficients, KF and RSF are used and its implementation is given in the following subsections.

4.1 Channel Estimation with Kalman Filter

Kalman filter is a recursive minimum mean square error (MMSE) estimator and it provides optimal estimation solution for linear and unbiased process with additive white noise. There is enough literature on KF, for example [1]. The implementation of KF for channel estimation problem given in above subsection is given in detail as following steps.

Kalman Filter Algorithm:

Filter initialization

$\hat{h}[n-1|n-1] = \mu_h$ and $P[n-1|n-1] = C_h$

Prior state estimation

$$\hat{h}[n|n-1] = A\hat{h}[n-1|n-1] \quad (14)$$

Prior estimate error covariance

$$P[n|n-1] = AP[n-1|n-1]A^T + Q \quad (15)$$

Kalman Filter gain

$$K[n] = P[n|n-1]V[n](V[n]^T P[n|n-1]V[n] + (R)^{-1} \quad (16)$$

Posterior state estimate

$$\hat{h}[n|n] = \hat{h}[n|n-1] + K[n]\left(x[n] - V[n]^T\hat{h}[n|n-1]\right) \quad (17)$$

Posterior estimate error covariance

$$P[n|n] = (I - K[n]V[n]^T)P[n|n-1] \quad (18)$$

4.2 Proposed Risk Sensitive Filter Approach

A RSF which is recursively updates posteriori state and estimate error covariance as given in [26, 24] is used here for fading channel estimation. Implementation of fading channel estimation using RSF is as follows

For linear system, the posteriori state estimate $\hat{h}$ of h at k^{th} time is obtained by the risk sensitive approach such that

$$\hat{h} \in \arg\min_{\varsigma} E[\exp\theta\{\sum_{m=0}^{k-1} l(h_m,\hat{h}_m) + l(h_m,\varsigma)\}|x[n]] \quad (19)$$

Here, θ is a tuning parameter, known as risk factor or risk parameter, the function $l(h,\hat{h})$ is defined as

$$l(h,\hat{h}) = \frac{1}{2}(h-\hat{h})^T(h-\hat{h}) \quad (20)$$

$$x[n] = \{x[1],..,x[n]\} \quad (21)$$

(Notation T denotes transpose) This is strictly filtering problems. For more details readers can refer [2, 27, 26].

As [26], posteriori state estimation given as

$$\hat{h}[n|n] = A\hat{h}[n-1|n-1] + P[n|n]V[n]^T R^{-1}(x[n] - V[n]^T A\hat{h}[n-1|n-1]) \quad (22)$$

Posteriori estimation risk error covariance is given as

$$P[n|n]^{-1} = [A(P[n-1|n-1]^{-1} - \theta I)^{-1}A^T + Q]^{-1} + V[n]R^{-1}V[n]^T \quad (23)$$

4.3 CRLB's for Channel Estimation

CRLB is a theoretical performance bound used to measure the accuracy of estimation filters. It gives lower limits on estimate error covariance in the form of information matrix. As detail theory and derivation on CRLB are out of scope in this work, it is not elaborated that in this section and if readers are interested, it is requested to refer [1, 29]. Implementation of CRLB to estimate the time varying coefficients in channel model is given as follow:

$$J[n+1] = Q[n]^{-1} + V[n+1]R[n+1]^{-1}V[n+1]^T - Q[n]^{-1} A[n](J[n] + A[n]Q[n]^{-1}A[n]^T)^{-1}A[n][Q[n]^{-1}]^T$$

5 Numerical Simulations

Numerical simulation of fading channel estimation using KF and RSF is studied with two cases; normal channel model and with uncertainty channel model. Waveform simulation is performed here for qualitative analysis of channel estimation. The Root mean square error (RMSE) with Monte Carlo runs is presented in this section.

Case 1. Nominal (autoregressive) Channel Model

In nominal case, slow fading channel environment the AR model parameter takes values 0 to 1. Keeping this in mind we assume the following numerical values to analyze the waveform simulation of fading channel.

Assume $p = 2$, $A = \begin{bmatrix} 0.99 & 0 \\ 0 & 0.999 \end{bmatrix}$,

$Q = \begin{bmatrix} 0.0001 & 0 \\ 0 & 0.0001 \end{bmatrix}$, $R = 0.1$,

The input and output of the considered channel problem is depicted in fig.3.

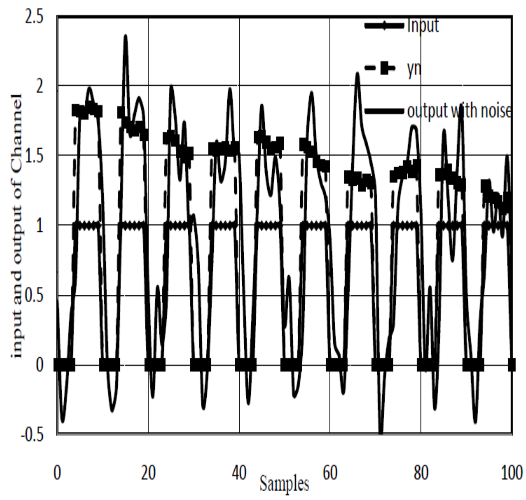

Fig.3 Input and output of Fading Channel

The risk factor of sensitive filter is tuned to estimate channel taped gains $h_0[n]$ and $h_1[n]$. In this problem the value of risk factor is considered as $\theta = 0.5805$. The performance of KF and RSF are compared and it is found that the performance of both is outstanding as given in [1]. Therefore, much more discussion on it is not given here.

Case 2. Uncertainty (random walk) Channel Model

This case study is at worst case, where the slow fading breaks i.e symbol duration is higher than the coherence time The assume numerical values are as follows:

$$p = 2, \qquad A = \begin{bmatrix} 0.99 & 0 \\ 0 & 0.999 \end{bmatrix},$$

$$Q = \begin{bmatrix} 0.0001 & 0 \\ 0 & 0.0001 \end{bmatrix},$$

$$R = 0.1, \quad \Delta A = \begin{bmatrix} 0 & del \\ 0 & 0 \end{bmatrix}, \quad -1 < del < 1.$$

Value of *del* is varied from either to the side of zero or to one. Fig.4 shows the input and output, with noise and without noise, when del=0.5.

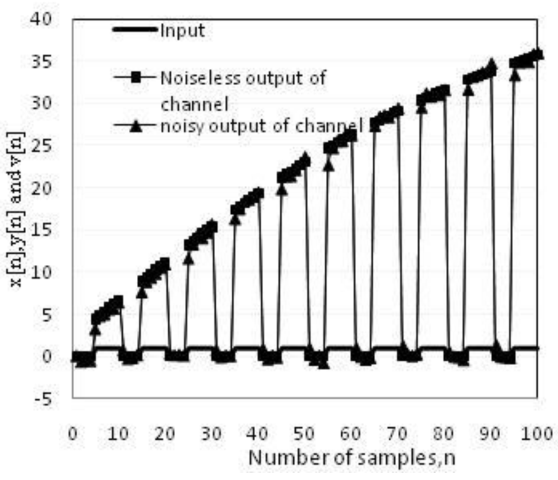

Fig.4 Input and output of Fading Channel under uncertainty with *del*=0.5

The Root mean square error (RMSE) performance for estimation of $h_0[n]$ and $h_1[n]$ of channel using KF and RSF is studied. Fig.5 and fig.6 shows the RMS value at last i.e in this case 100th sample against various *del* for $h_0[n]$ and $h_1[n]$ estimation are shown. Figure 5 and 6 shows slight improvement in the performance by RSF over the performance of KF. It is because the risk present is cost function due to uncertainty. Thus robustness, against uncertainty in the channel model, of risk sensitive filter over Kalman filter, fine tuning is achieved.

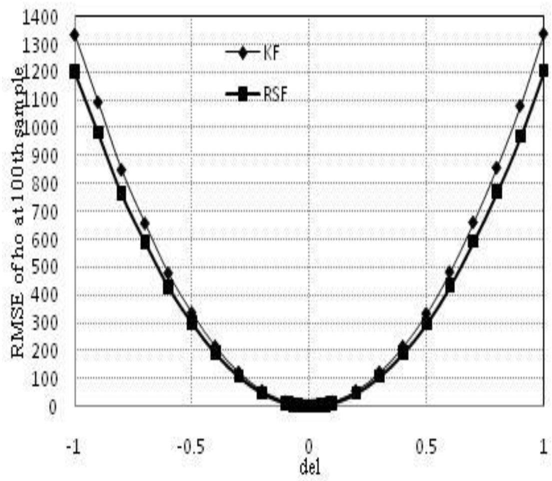

Fig.5 Comparison of RMSE at 100th sample for $h_0[n]$ (h0) estimation by KF and RSF

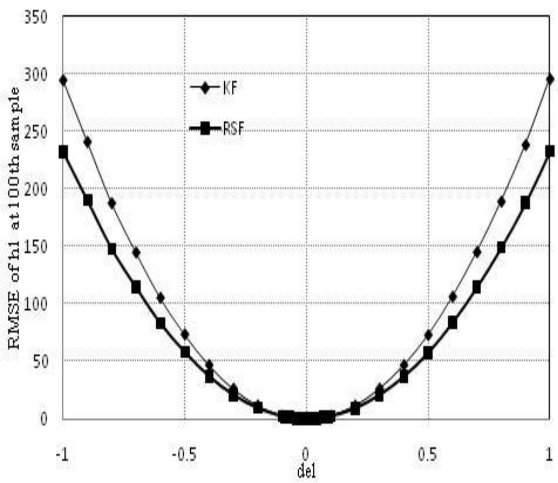

Fig.6 Comparison of RMSE at 100th sample for $h_1[n]$ (h1) estimation by KF and RSF

It is clear that channel measurement is possible and reliable if *del* value is taken close to zero. This channel can be estimated with robust risk sensitive filter. The RMSE performance comparison of KF and RSF is graphically exemplified in figure.7 and figure.8. Form this figures it is clear that risk sensitive filter results good as compared to KF when there is uncertainty. The RMSE obtained by RSF is close to follow CRLB, where KF is not. The CRLB is taking account of uncertainty present in system model.

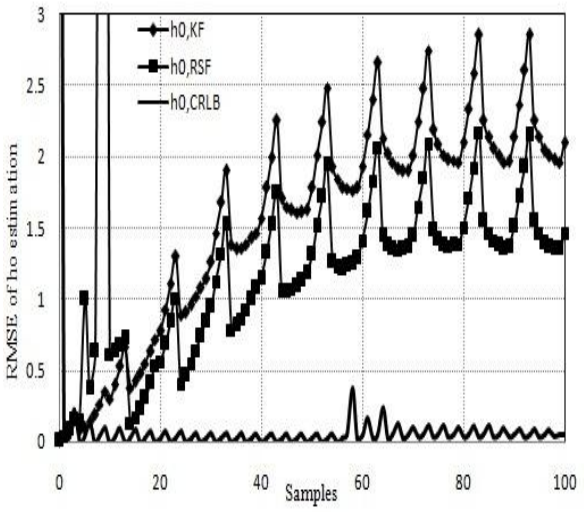

Fig.7 Comparison of CRLB and RMSE for $h_0[n]$ (h0) estimation by KF and RSF

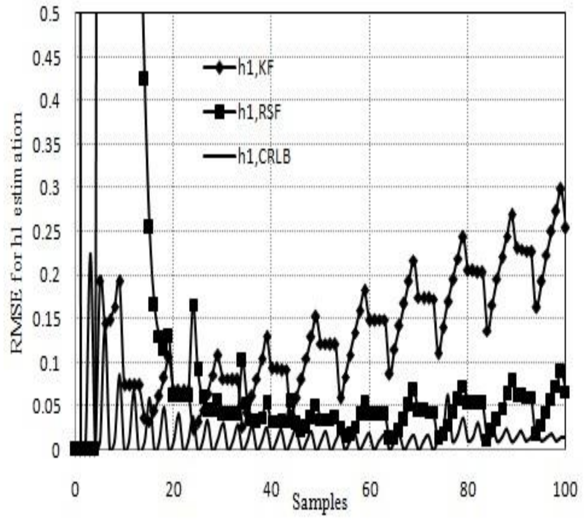

Fig.8 Comparison of CRLB and of RMSE for $h_1[n]$ (h1) estimation by KF and RSF

To study the robustness against Q variations in channel model, the value of Q factor is varied from 0 to 2000. Figure 9 and 10 shows that the performance of risk sensitive filter is marginally better, particularly in the case of h1, than the KF, when Q factor is increased. The value of Q factor is varied from 0 to 2000.

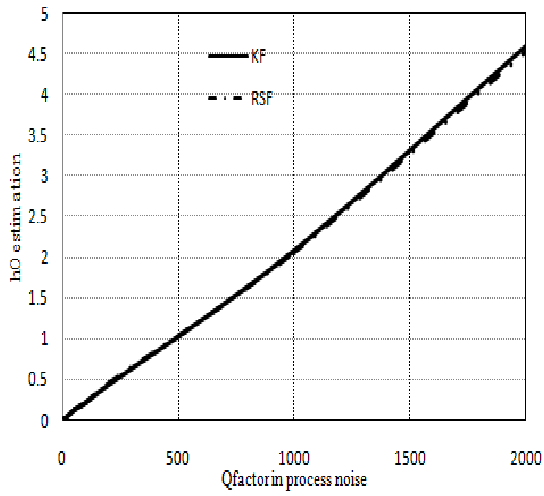

Fig.9 RMSE comparison for $h_0[n]$ (h0) estimation by KF and RSF

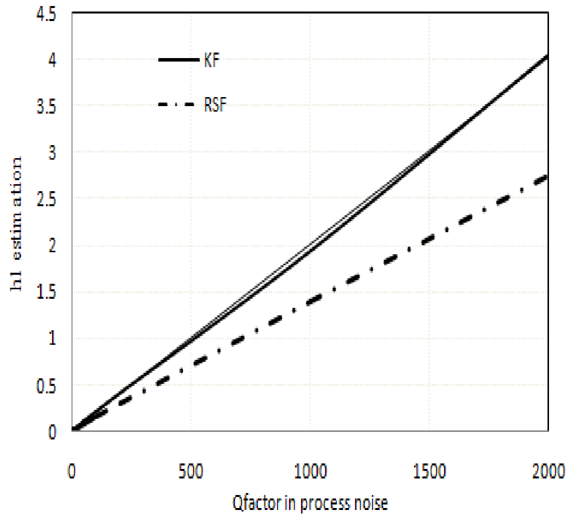

Fig.10 RMSE comparison for $h_1[n]$ (h1) estimation by KF and RSF

6 Discussion and Conclusion

The Risk factor present in the risk sensitive filter has allowed reshaping the probability density of estimated variables, so that it is required a fine tuning to achieve robust performance, when uncertainty is present in the channel, in fading channel estimation. Fading channel estimation with two different scenarios; nominal channel model and parameter uncertainty in channel model, is elucidated. With large Monte Carlo runs, simulation has been studied and results were compared. At limited level of uncertainty in parameter and process noise variance of channel model, the risk sensitive filter is robust as compared to Kalman filter. Performance of channel estimation obtained by risk sensitive filter and Kalman filter were compared with theoretical performance bound using Cramer-Rao lower bound (CRLB) and the performance obtained by RSF try to follow CRLB, whereas the performance obtained by KF is does not. When channel loosing slow fading nature. i.e *del* value is very near to zero, the risk sensitive filter can be effectively used as robust channel estimation.

Thus the proposed work may be an alternative and an efficient method to estimate the time varying channel for modern OFDM and MIMO-OFDM considering more uncertainty in parameter and process noise to improve the bit error rate and mean square error for better performance.

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