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Adaptive tracking of narrowband HF channel response

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[1] Estimation of channel impulse response constitutes a first step in computation of scattering function, channel equalization, elimination of multipath, and optimum detection and identification of transmitted signals through the HF channel. Due to spatial and temporal variations, HF channel impulse response has to be estimated adaptively. Based on developed state-space and measurement models, an adaptive Kalman filter is proposed to track the HF channel variation in time. Robust methods of initialization and adaptively adjusting the noise covariance in the system dynamics are proposed. In simulated examples under good, moderate and poor ionospheric conditions, it is observed that the adaptive Kalman filter based channel estimator provides reliable channel estimates and can track the variation of the channel in time with high accuracy. *INDEX TERMS:* 2487 Ionosphere: Wave propagation (6934); 2494 Ionosphere: Instruments and techniques; 6964 Radio Science: Radio wave propagation; 6974 Radio Science: Signal processing; *KEYWORDS:* HF channel, adaptive tracking, Kalman filter

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1. Introduction

[2] Estimation of channel impulse response is an important ingredient in the design of reliable communication systems. The estimation process constitutes a first step in computation of scattering function, channel equalization, elimination of multipath, and optimum detection and identification of transmitted signals. The estimation of channel impulse response is a major challenge for noisy multipath channels that also vary both in spatial and temporal domains. The HF communication channel and underwater acoustic channel are the two examples where channel estimation has to performed adaptive to time variations of the channel. In HF band, due spatial and temporal variations at various scales, the channel response is usually obtained by controlled experiments conducted for specific links and frequency intervals of interest. In these experiments, typically, a predetermined narrowband input sequence is transmitted and the variability of the channel investigated based on the observed channel output sequence. This investigation requires the adaptive estimation of the channel response where the adaptation should be fast enough to capture the short term variations in the channel response.

[3] Kalman filter can be utilized as an ideal processing tool for estimation of the HF channel response [*Proakis*, 1995; *Haykin*, 1991; *Clark*, 1989]. However, Conventional Kalman Filters, as mentioned in *Clark* [1989], are operated with little or no adaptation to the physical structure of the channel. Since the performance of the Kalman Filter is very sensitive to the dynamics of the channel, careful initialization and proper adjustments of the operating parameters are required for improved performance [*Haykin*, 1991; *Arikan and Arikan*, 1998; *Miled and Arikan*, 2000]. In this paper, a robust method for the initialization of the Kalman filter is proposed. The measurement noise covariance matrix is modeled in an adaptive manner that represents the underlying varying physical structure of the ionosphere. The performance of the estimation algorithm is tested with the channel outputs obtained from simulated HF links under good, moderate and poor ionospheric conditions. With the new state-space model to capture the pulse-to-pulse variability of the channel impulse response and initialization, the tracking performance of the Kalman filter improved significantly compared to that of the Conven-

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tional Kalman Filter even under poor ionospheric conditions. According to *Clark* [1989], the major problems in application of conventional Kalman Filters can be summarized as the cost of implementation, computational complexity, tendency of a steady build-up of round-off errors compared with other possible estimators. All these problems can be overcome with new fast and cost-effective Digital Signal Processors.

[4] In Section 2, formulation of the state space model and the Kalman Filter will be presented. Also, the initialization of the Kalman filter parameters which considerably affects the performance of tracking will be discussed in detail. In Section 3, results for a computer simulated channel will be presented.

2. Estimation of Baseband Channel Response

[5] For the multipath fading channels, which vary with time, space and frequency, the down converted channel output $r(t)$ corresponding to an arbitrary input signal $a(t)$ can be expressed as

$$r(t) = \int_0^\infty a(t-\tau)h(t;\tau)d\tau \qquad (1)$$

where $h(t;\tau)$ is the baseband equivalent of the causal but time varying impulse response of the channel. Specifically, $h(t;\tau)$ is the response of the channel to an impulsive input at time $t - \tau$ [*Proakis*, 1995]. Causality of the channel response implies that: $h(t;\tau) = 0$ for $\tau < 0$.

[6] In order to estimate the baseband channel response, the data obtained from controlled experiments can be used. In these controlled experiments, typically the channel input is chosen as a modulated pulse train: $a(t) = \sum_{p=0}^{N_p-1} a_p s(t - pT_p)$, where N_p is the total number of pulses, T_p is the pulse period, a_p is the known information bit for p^{th} pulse, and $s(t)$ is the pulse waveform. The corresponding channel output in equation (1), can be expressed as in the following vectoral notation:

$$r(t) = \sum_{p=0}^{N_p-1} a_p \mathbf{s}_{p,t}^T \mathbf{h}_t + v(t) \qquad (2)$$

where $v(t)$ is the additive measurement noise, ^{T} is the transposition operator, and the vectors $\mathbf{s}_{p,t}$ and $\mathbf{h}_t$ are defined as

$$\mathbf{s}_{p,t} = \frac{T_p}{M}\left[s(t-pT_p)\ \ldots\ s(t-pT_p-LT_p)\right]^T \qquad (3)$$

and

$$\mathbf{h}_t = \left[h(t;0)h\left(t;\frac{T_p}{M}\right)\ \ldots\ h\left(t;\left(L-\frac{1}{M}\right)\frac{T_p}{M}\right)\right]^T. \qquad (4)$$

In the above equations, T_p/M is the time sampling interval, which is chosen to be short enough for negligible aliasing in the obtained samples of $a(t)$ and $h(t;\tau)$. LT_p is the maximum duration of $h(t;\tau)$ in delay domain. The length of $h(t;\tau)$ in delay domain depends on the structure of the ionosphere. For poor conditions, LT_p is longer than those values for moderate and good conditions. In Section 3, these lengths will be compared for a simulated channel.

[7] In the experiments conducted over the ionospheric channel, the output signal is recorded and digitized in the form of samples of as shown below:

$$r(n) = r\left(n\frac{T_p}{M}\right) = \sum_{p=0}^{N_p-1} a_p \mathbf{s}_{p,n}^T \mathbf{h}_n + v\left(n\frac{T_p}{M}\right). \qquad (5)$$

This relation between the discrete channel inputs and outputs can be conveniently represented as in the following state space model:

$$\mathbf{h}_{n+1} = \mathbf{A}\mathbf{h}_n + \mathbf{u}_n \qquad (6)$$

$$r(n) = \mathbf{C}_n^T \mathbf{h}_n + v(n) \qquad (7)$$

In the above model, equation (6) is called as the process equation. The matrix $\mathbf{A}$ is defined as the state of the system at times $n + 1$ and n. The vector $\mathbf{u}_n = \mathbf{u}(n\frac{T_p}{M})$ represents the process noise which can also be defined as the time variation on $\mathbf{h}_n$. Equation (7) is known as the measurement equation and $\mathbf{C}_n$, where $\mathbf{C}_n = \sum_{p=0}^{N_p-1} a_p \mathbf{s}_{p,n}$, is called as the measurement matrix. $v(n)$ in equation (7) is called as the measurement noise which is usually modelled as a zero mean, white noise process.

[8] In the above state-space model, $\mathbf{h}_n$ can vary within a pulse interval. However, in HF applications the time variation of the channel response can be safely modeled to vary on a pulse-to-pulse basis [*Arikan and Erol*, 1998]. Under this assumption, we can obtain the following simplified model where variations in $\mathbf{h}$ is modelled to take place from pulse-to-pulse, where the impulse response of the ionosphere is allowed to vary according to $\mathbf{u}_p$, a predefined time variation on $\mathbf{h}_p$ as

$$\mathbf{h}_{p+1} = \mathbf{h}_p + \mathbf{u}_p \qquad (8)$$

$$\mathbf{r}_p = \mathbf{C}_p^T \mathbf{h}_p + \mathbf{v}_p \qquad (9)$$

where the subscript p denotes the p^{th} pulse. The matrix $\mathbf{A}$ in equation (6) is chosen as an $LM \times LM$ identity matrix.

[9] Based on this state-space model, the mean squared optimal estimation of the channel response $\mathbf{h}_{p+1}$ can be carried out efficiently by using the well known Kalman Filter algorithm [*Haykin*, 1991]. However, the overall performance of the Kalman filter heavily depends on the

choice of the initial conditions and the correlation of $\mathbf{u}_p$, $\mathbf{R_u}(p)$.

[10] Initialization of Kalman Filter consists of one of the most important steps in convergence and stability of the algorithm. In the applications given in *Clark* [1989], the Kalman Filter was introduced to estimate the various parameters of the ionospheric channel. The Kalman Filter in *Clark* [1989] was initialized by a zero vector assuming that the estimator has no prior knowledge of the channel. However, in our application, we introduced a delay in the computational procedure, and initialized the Kalman Filter by making use of channel dynamics. We employed the Regularized Least Squares estimator in determining the initial channel impulse response by making use of the first few channel outputs as

$$\mathbf{h}_0 = \left(\mathbf{C}_0^H \mathbf{C}_0 + \mu \mathbf{I}\right)^{-1} \mathbf{C}_0^H \mathbf{r}_0. \tag{10}$$

In the above equation, the subscript 0 denotes the first *LM* number of samples of the received signal; and the superscript *H* indicates the Hermitian. With this initialization procedure, the Kalman Filter can operate with an initial estimate which minimizes the error between the actual channel and the estimated impulse response, provided that the channel is slowly varying at least for couple of pulses used in the initialization. This assumption seems to be valid for midlatitude links whose wide sense stationarity period is found to be in the order of 20 s [*Arikan and Erol*, 1998]. This delay in estimation causes the first channel estimate to be available only after first *LM* samples length of channel impulse response. In the next section, we will discuss the specific values of possible *LM* samples for a simulated channel. The Least Squares estimation is a well known technique [*Haykin*, 1991]. Yet, the problem of noise amplification for the cases when $\mathbf{C}_p^T$ in equation (9) has a large condition number, is a major drawback. In order to avoid this difficulty, we have introduced a regularization parameter, μ, and employed Tickhonov regularization algorithm [*Colton and Kress*, 1992; *Donoho*, 1994]. The regularization parameter μ can be chosen as a preset value or it can be determined by examining the channel dynamics for the initial condition estimation. A more robust way of choosing the regularization parameter μ is by examining the singular values of the matrix $\mathbf{C}_0^H \mathbf{C}_0$ for various ionospheric conditions. The singular values will be obtained in descending order and the optimum point for μ can be chosen according to the break point of the singular values where there is a major variation from the significant to insignificant singular values. An example of this procedure of choosing μ will be provided in the next section for a simulated ionospheric channel. In our application, equation (10) is only used to initialize the Kalman Filter and the Kalman Filter further refines the estimates of the impulse response as new samples become available.

[11] The second parameter which plays a critical role in the overall performance of the Kalman channel estimator is $\mathbf{R_u}(p)$, the correlation function of the noise in system dynamics. Again, in previous applications of Kalman estimator for the ionospheric channel such as in *Clark* [1989], $\mathbf{R_u}(p)$ is either chosen as a constant matrix or the adaptation is not based on the channel dynamics. Unlike previous approaches, in the presented algorithm, the innovation in the channel impulse response is modelled such that there is a larger variability around the peaks of the channel impulse response. Thus, we propose the following time-varying form for the $\mathbf{R_u}(p)$:

$$\mathbf{R_u}(p) = \frac{\sigma_u^2}{\| \mathbf{h}_{p-1} \|^2} \begin{bmatrix} k_1 & 0 & \cdots & 0 \\ 0 & k_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & k_{LM} \end{bmatrix} \tag{11}$$

where

$$k_i = \left(\left|\mathbf{h}_{p-1}(i-1)\right|^2 + 2\left|\mathbf{h}_{p-1}(i)\right|^2 + \left|\mathbf{h}_{p-1}(i+1)\right|^2\right)/4, \tag{12}$$

and $i = 1, \ldots, LM$. This form of $\mathbf{R_u}(p)$ not only varies from pulse-to-pulse but also adjusts itself to the variations in the delay domain, reflecting the actual time variation of HF modes, where the channel response shows greater variation in the vicinity of the peaks that occur at refraction points. With this model, we tried to capture the actual dynamics of the HF channels.

[12] As will be demonstrated in the following section, this adaptation of Kalman Filter parameters to the physical variations in the channel significantly improves the performance.

3. Results for a Simulated HF Channel

[13] The channel output, $r(t)$, can be obtained either from controlled experiments for a specific HF link or by proper simulation of HF channel response. Even for the cases where experimental data are available, simulations are generally preferred to test the performance of the proposed algorithms due to the fact that the original channel response is exactly known. Both ordinary and extreme ionospheric conditions can be realized with a proper simulation model. For the time varying HF channel impulse response, various alternative models are available including *Watterson et al.* [1970], *International Telecommunication Union* (*ITU*) [1998], and

Table 1. Parameters for Good, Moderate, and Poor Conditions for Simulated HF Channel

	Good		Moderate		Poor	
Parameter	Tap 1	Tap 2	Tap 1	Tap 2	Tap 1	Tap 2
τ (msec)	0	0.5	0	1	0	2
σ_a	0.05	0.05	0.25	0.25	0.5	0.5
σ_b	0.05	0.05	0.25	0.25	0.5	0.5
A_a	1	1	1	1	1	1
A_b	1	1	1	1	1	1
f_a (Hz)	0	0	0	0	0	0
f_b (Hz)	0	0	0	0	0	0
σ_t (msec)	0.25	0.25	0.5	0.5	1	1

Bertel et al. [1996]. Any of these models can be used in the simulation program. In this study, the simulation model is based on the model proposed in *Watterson et al.* [1970] since representing the channel response only in time is sufficient for us to test the performance of the Kalman Filter. In the Watterson channel model, a Finite Impulse Response (FIR) filter is used to generate tap coefficients in delay for each sampling interval in time. The parameter set for simulation is obtained from *International Telecommunication Union Radiocommunicaton* (*ITU-R*) [1992]. The summary of the parameters of the Watterson model for 'good,' 'moderate' and 'poor' ionospheric conditions are provided in Table 1. In Table 1, the parameter τ in msec represents the delay between two taps of the FIR filter corresponding to reflections from two different ionospheric layers for good, moderate and poor conditions. For each time sample and at each tap, the delayed signal is modulated in amplitude and in phase by an appropriate complex random tap gain function. The delayed and modulated signals are summed with additive noise to form the received signal. Each tap gain function is a sum of two magnetoionic components denoted by subscripts *a* and *b* as denoted in Table 1. Each magnetoionic component is obtained by multiplying a sample function of an independent complex Gaussian ergodic random process with zero mean by an exponential factor to provide the desired Doppler (frequency) shifts of the tap gain spectrum. In Table 1, these frequency shifts are denoted by f_a and f_b for the two magnetoionic components, respectively. In Table 1, the parameters A_a and A_b represent the component attenuation of the spectrum of the tap gain function. The frequency spread on each component is determined by $2\sigma_a$ and $2\sigma_b$, for the two magnetoionoic components, respectively, as given in Table 1 for the good, moderated and poor ionospheric conditions. In this FIR filter model, the ionospheric reflections are assumed to take place at a specific height, so channel impulse response is represented as impulses in the delay domain. Yet, we believe including the thickness of reflecting layers is a better physical model. Thus, the model for the impulse response in *Watterson et al.* [1970] is modified by adding a spread function to represent the effect of thickness of the ionospheric layers. In the modified Watterson model, we have multiplied the tap coefficients with a spread function and superposed the spread functions with appropriate time delays at the filter output. The amount of delay spread (σ_t in Table 1) is determined from published measurements on HF channel such as *Lundborg et al.* [1996]. For a fixed observation time t_0, typical forward the channel impulse response for good, moderate and poor conditions, $|h(t_0; \tau)|$, is provided in Figure 1. In our simulations, the maximum duration of $|h(t; \tau)|$ in delay domain extends as $L = 2$ pulses for the good condition; $L = 4$ pulses for the moderate condition; and $L = 6$ pulses for the poor condition of the ionosphere.

[14] The Kalman Filter algorithm discussed in the previous section is used to estimate the forward HF channel model. The percent error of the estimator for p^{th} pulse is determined by

$$e(p) = \frac{\| \mathbf{h}_{wp} - \mathbf{h}_p \|}{\| \mathbf{h}_{wp} \|} \times 100 \qquad (13)$$

where $\mathbf{h}_{wp}$ is the output of modified Watterson channel forward model, $\mathbf{h}_p$ is the Kalman Filter estimate, and $\| . \|$ denotes the $\mathcal{L}_2$ norm.

[15] For proper operation of the Kalman Filter, the first step is the determination of initialization conditions and the regularization parameter, μ, that is defined in equation (10) and used in estimation of $\mathbf{h}_0$. As mentioned in the previous section, a more robust way of choosing the regularization parameter μ is by examining the singular values of the matrix $\mathbf{C}_0^H\mathbf{C}_0$ for various ionospheric conditions and for various Signal-to-Noise Ratios (SNR) (10 dB to 40 dB). The singular values will be obtained in descending order and the optimum point for μ can be chosen according to the break point of the singular values where there is a major variation from the significant to insignificant singular values. For example, for the simulated ionospheric channel with parameters provided in Table 1, the singular values of $\mathbf{C}_0^H\mathbf{C}_0$ for the good condition are obtained as $[8.996 \times 10^{-8}\ 1.085 \times 10^{-8}\ 0.462 \times 10^{-8}\ 0.307 \times 10^{-8}\ 0\ 0\ 0\ 0]$. The break point of these singular values is 1.085×10^{-8} which is taken as the optimum value for μ. Similarly, the value of μ is determined as 0.8×10^{-8} for moderate conditions and 0.14×10^{-8} for poor ionospheric conditions.

[16] The second step is the appropriate determination of σ_u in equation (11). We checked the number of iterations that are necessary for convergence of the Kalman Filter algorithm and the error at convergence point with the forward model. In Figure 2, the number of iterations for convergence and the error for various

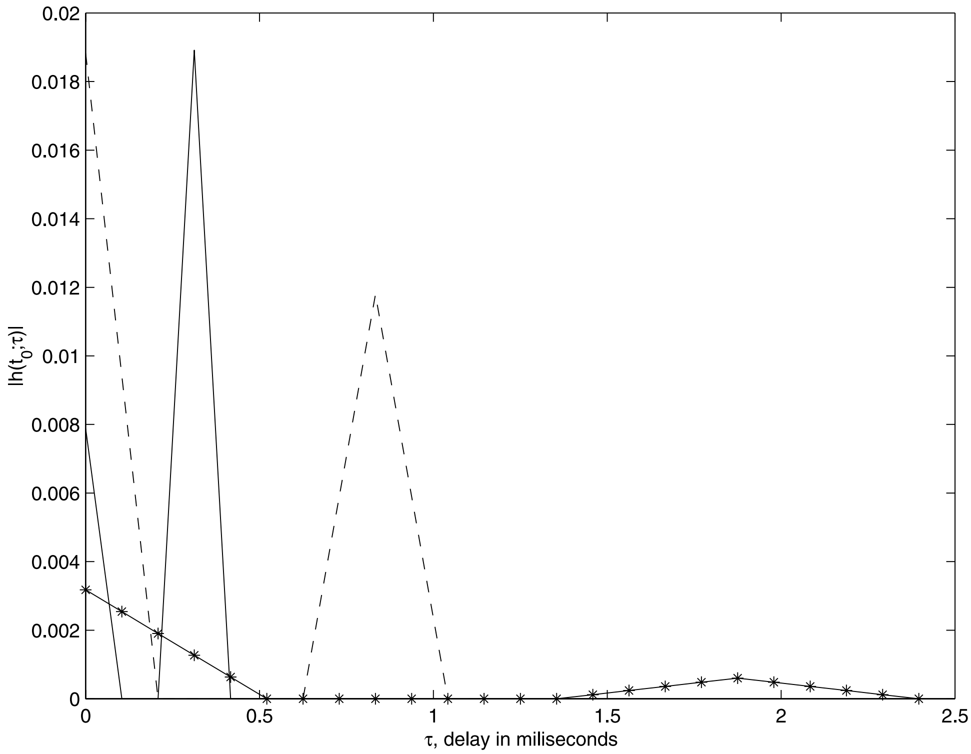

Figure 1. The forward channel impulse responses for good condition (solid line), moderate condition (dashed line) and poor condition (asterisks line).

SNR are plotted with respect to σ_u for good, moderate and poor conditions. σ_u is allowed to vary in a range of 10^{-3} to 10^{-1} for SNR 10 dB, 20 dB, 30 dB and 40 dB for good, moderate and poor ionospheric conditions. It is observed from Figure 2 that for good condition, number of iterations for convergence and error at convergence point are lowest compared to moderate and poor conditions. For high SNR values at good and moderate conditions, number of iterations for convergence are the smallest. For all conditions, high SNR values correspond to lowest error at convergence point. In all cases, although number of iterations for convergence decreases with increasing σ_u, error at convergence also increases. From Figure 2, it is determined that $\sigma_u = 10^{-3}$ is a reasonable choice for all conditions and SNRs since Kalman Filter converges faster to the lowest error.

[17] With the selected parameters, $\mathbf{R_u}(p)$ can be chosen to be constant as in *Clark* [1989] and *Clark and Hariharan* [1990] or to be adaptive as given in equation (11). It has been observed that when $\mathbf{R_u}(p)$ is adjusted to the varying conditions of the channel, even in poor ionospheric conditions and low SNRs, the estimator still converges successfully, tracking the variations in the channel both in delay and observation time. This effect is demonstrated by an example presented in Figure 3, by plotting the percent error defined in equation (13) for a number of iterations in the case of poor ionospheric conditions and SNR = 30 dB. In order to compare the convergence rate for the two approaches, the error bounds for the two cases are obtained. The middle horizontal solid line in Figure 3 denotes the mean of 2048 error samples of the adaptive Kalman Filter. The error for the adaptive case is bounded within the two standard deviation interval that are indicated by the upper and lower horizontal solid lines in Figure 3. It is apparent from Figure 3 that both the mean and the error bounds for the conventional non-adaptive case are significantly higher than those for the adaptive case.

[18] The Least Squares (LS) algorithm is widely preferred as an estimator due to its ease in implementation and low computational complexity. In order to compare the advantages and disadvantages with those of the Kalman Filter estimator, we implemented the LS channel impulse response estimate as

$$\widehat{\mathbf{h}} = \left(\mathbf{C}_a^H \mathbf{C}_a\right)^{-1} \mathbf{C}_a^H \mathbf{r}_a \qquad (14)$$

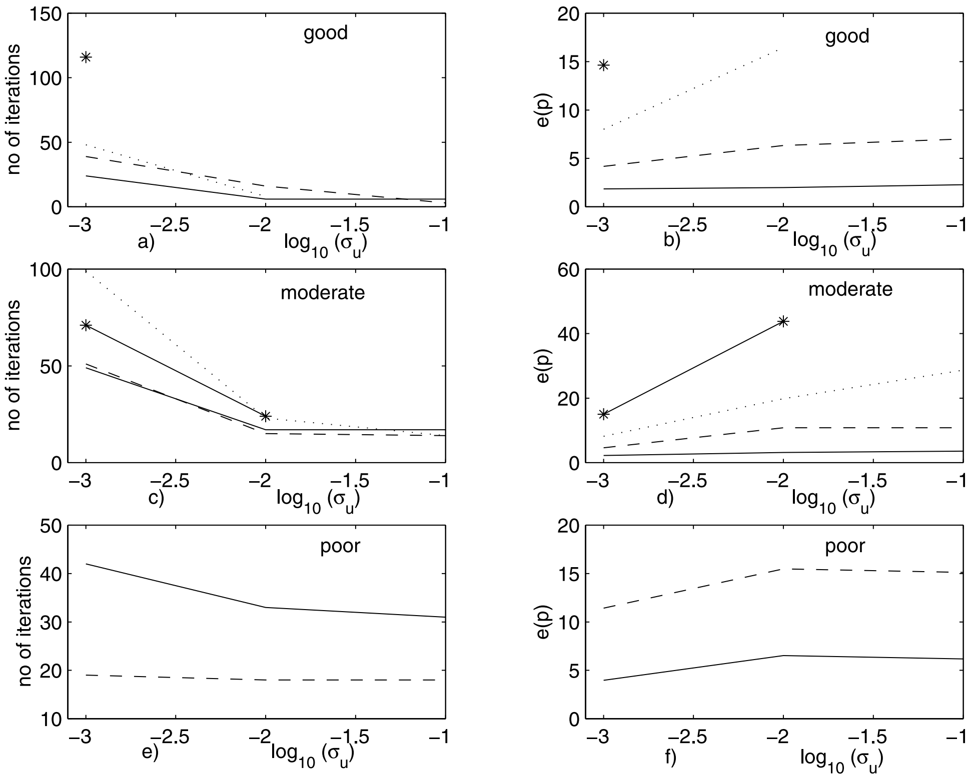

Figure 2. Number of iterations for convergence and percent error at convergence for good, moderate and poor conditions for SNR's 40 dB (solid line), 30 dB (dashed line), 20 dB (dotted line), and 10 dB (asterisks line).

where the subscript a denotes the number of pulses that are included in the computation. For comparison of these two estimators, we have conducted a large set of simulations. It is observed that the least squares method converges faster with a lower convergence error when compared to the Kalman Filter method for good conditions where the channel does not change from pulse-to-pulse. For moderate and poor conditions, the least squares method fails whereas Kalman Filter still converges with a reasonable error and is capable of tracking the variations of the channel.

[19] The error plots for convergence for Kalman Filter at various ionospheric conditions and for various SNRs are shown in Figure 4. It is observed that with the suggested choice of parameters and initial conditions, the adaptive Kalman Filter estimator converges not only for good and moderate conditions and high SNRs but also for poor conditions of ionosphere and low SNRs.

[20] The advantage of the Least Square method is apparent in an off-line estimation of channel response for a time invariant HF link since the information of the invariant channel is inherently built in the Least Squares solution. When the channel is time varying and/or the estimation needs to be performed in real time, Kalman Filter is advantageous since the estimates can track the variations in the channel. The relatively high computational complexity of Kalman Filters are reduced significantly owing to the rapid development of fast and cost-effective Digital Signal Processors.

4. Conclusions

[21] The characterization of narrowband HF channel response is an important ingredient in the design of HF communication systems. In this paper, we propose a Kalman filter based channel estimator that can be efficiently used to track the variations in the ionospheric channel response. The innovative contribution of the proposed estimation method is in the choice of physically meaningful ways of initialization and adaptation parameters of the Kalman filter. The initial conditions are determined by using Least Squares algorithm on channel measurements. The correlation of the variation on the channel response is modified

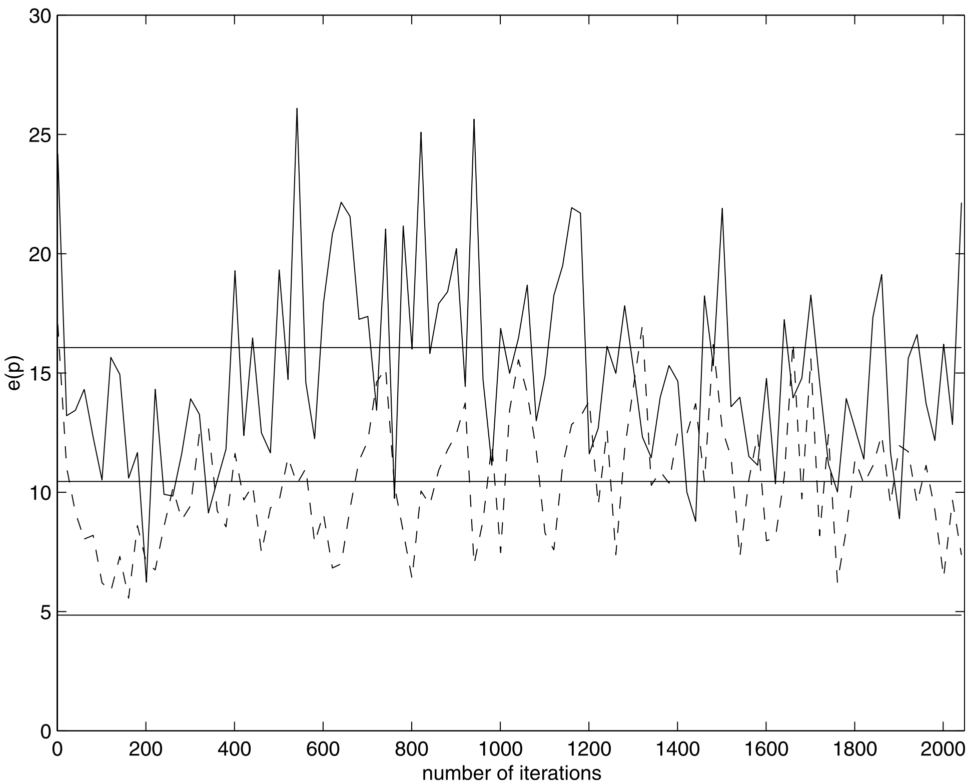

Figure 3. Error plot for convergence for poor ionospheric conditions and 30 dB SNR when $\mathbf{R_u}(p)$ chosen to be adaptive (dashed line) and when $\mathbf{R_u}(p)$ chosen to be constant (solid line).

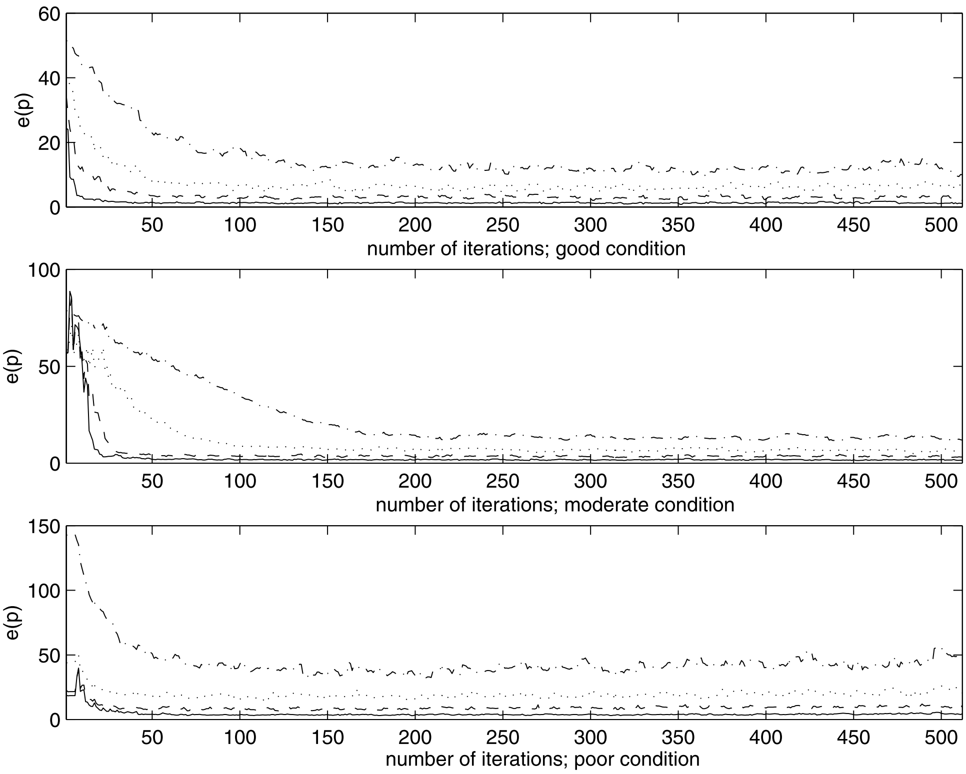

Figure 4. Error plots for convergence for good, moderate and poor conditions for SNR's 40 dB (solid line), 30 dB (dashed line), 20 dB (dotted line), and 10 dB (dash-dotted line).

to vary adaptively from pulse to pulse as a function of past estimates. Based on simulations of HF channels under various ionospheric states and SNRs, it has been observed that the suggested method significantly improves the performance compared to the Conventional Kalman filter estimator where the ionospheric system dynamics and robust initialization routines are not incorporated. Once the channel impulse response is reliably estimated, the communication system can perform other tasks such as the computation of the scattering function and channel equalization.

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