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Implementation of New Approach of Kalman Filter for Highly Noise Resistive Communication

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Abstract—*Signals are carriers of information, both useful and unwanted. Extracting or enhancing the useful information from a mix of conflicting information is a simplest form of signal processing. Acoustic noise problems becomes more pronounce as increase in number of industrial equipment such as engines, transformers, compressors and blowers are in use. An adaptive filter is a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. Adaptive filtering is a wide area of researcher in present decade in the field of communication. Adaptive noise cancellation is an approach used for noise reduction in speech signal. This paper works we presents an algorithm for performing effective channel estimation for multiple inputs multiple outputs (MIMO), the channel estimation is performed using an proposed Extended Kalman Filter (EKF).*

1. INTRODUCTION

ORTHOGONAL frequency division multiplexing (OFDM) is a multi carrier modulation scheme where a single data stream is transmitted using N orthogonal subcarriers. The most important reasons for adopting OFDM as a 4G LTE mobile wireless standard are very high spectral efficiency and very high data rates, ability to inherently convert frequency selective fading channels to frequency flat fading channels, resistance to multi path and relatively simple equalization techniques. Multiple Input Multiple Output (MIMO) OFDM systems provide very high data rate and offer even better robustness to multipath. Hence, MIMO OFDM is the future of mobile wireless technology.

OFDM MIMO required three divisions –

- The MIMO OFDM modelling.
- The Autoregressive CA and CFO modelling and implementation of the filter.
- The channel estimation algorithm

Lots of research work has been done on all divisions as discuss above we are taking care of the second the implementation of Filter and our proposed filter is adaptive in nature which is an Extended Kalman filter we made necessary modification in the filter present design for better results.

Adaptive filter:-

An adaptive filter is a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. The notion of making filters adaptive, i.e., to alter parameters (coefficients) of a filter according to some algorithm, tackles the problems that we might not in advance know, e.g., the characteristics of the signal, or of the unwanted signal, or of a systems influence on the signal that we like to compensate. Adaptive filters can adjust to unknown environment, and even track signal or system characteristics varying over time. There lots of adaptive filters available like Least Mean Square (LMS), RLS (Recursive Least Square), Kalman and Extended Kalman.

The block diagram below, shown in the following figure, serves as a foundation for particular adaptive filter realisations, such as Least Mean Squares (LMS) and Recursive Least Squares (RLS. The idea behind the block diagram is that a variable filter extracts an estimate of the desired signal.

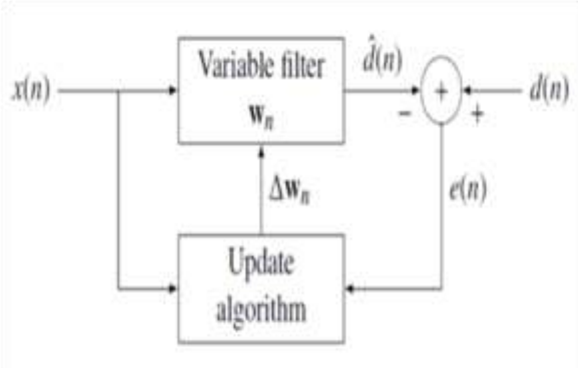

Figure 1 : Adaptive Filter

To start the discussion of the block diagram we take the following assumptions:

The input signal is the sum of a desired signal $d(n)$ and interfering noise $v(n)$

$$x(n) = d(n) + v(n)$$

The variable filter has a Finite Impulse Response (FIR) structure. For such structures the impulse response is equal to the filter coefficients. The coefficients for a filter of order p are defined as

$$\mathbf{w}_n = [w_n(0), w_n(1), ..., w_n(p)]^T$$

The error signal or cost functio is the difference between the desired and the estimated signal

$$e(n) = d(n) - \hat{d}(n)$$

The variable filter estimates the desired signal by convolving the input signal with the impulse response. In vector notation this is expressed as

$$\hat{d}(n) = \mathbf{w}_n * \mathbf{x}(n)$$

Where

$$\mathbf{x}(n) = [x(n), x(n-1), ..., x(n-p)]^T$$

is an input signal vector. Moreover, the variable filter updates the filter coefficients at every time instant

$$\mathbf{w}_{n+1} = \mathbf{w}_n + \Delta\mathbf{w}_n$$

where $\Delta\mathbf{w}_n$ is a correction factor for the filter coefficients. The adaptive algorithm generates this correction factor based on the input and error signals. LMS and RLS define two different coefficient update algorithms.

The Kalman filter, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. More formally, the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state.

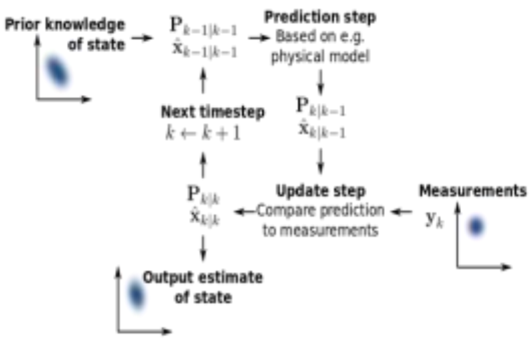

Figure 2 : Kalman Algorithm

The figure shown above is the basic working of an adaptive Kalman filter. The

Kalman filter keeps track of the estimated state of the system and the variance or uncertainty of the estimate. The estimate is updated using a state transition model and measurements. $\hat{x}_{k|k-1}$ Denotes the estimate of the system's state at time step *k* before the *k*-th measurement y_k has been taken into account; $P_{k|k-1}$ is the corresponding uncertainty.

In estimation theory, the extended Kalman filter (EKF) is the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance.

In the extended Kalman filter, the state transition and observation models need not be linear functions of the state but may instead be differentiable functions.

$$\boldsymbol{z}_k = h(\boldsymbol{x}_k) + \boldsymbol{v}_k$$

Where w_k and v_k are the process and observation noises which are both assumed to be zero mean multivariate Gaussian noises with covariance Q_k and R_k respectively.

The function *f* can be used to compute the predicted state from the previous estimate and similarly the function *h* can be used to compute the predicted measurement from the predicted state. However, *f* and *h* cannot be applied to the covariance directly. Instead a matrix of partial derivatives (the Jacobian) is computed.

At each time step, the Jacobian is evaluated with current predicted states. These matrices can be used in the Kalman filter equations. This process essentially linearizes the non-linear function around the current estimate.

PREDICT

Predicted state estimate

$$\hat{\boldsymbol{x}}_{k|k-1} = f(\hat{\boldsymbol{x}}_{k-1|k-1}, \boldsymbol{u}_{k-1})$$

Predicted covariance estimate

$$\boldsymbol{P}_{k|k-1} = \boldsymbol{F}_{k-1}\boldsymbol{P}_{k-1|k-1}\boldsymbol{F}_{k-1}^{\top} + \boldsymbol{Q}_{k-1}$$

UPDATE

Innovation or measurement residual

$$\tilde{\boldsymbol{y}}_k = \boldsymbol{z}_k - h(\hat{\boldsymbol{x}}_{k|k-1})$$

$$\boldsymbol{S}_k = \boldsymbol{H}_k\boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{\top} + \boldsymbol{R}_k$$

Innovation (or residual) covariance

$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{\top}\boldsymbol{S}_k^{-1}$$

Near-optimal Kalman gain

$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k\tilde{\boldsymbol{y}}_k$$

$$\boldsymbol{P}_{k|k} = (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H}_k)\boldsymbol{P}_{k|k-1}$$

Updated state estimate

Updated estimate covariance

2. METEDOLOGY

This paper studies the statistical behaviour of a unique combination of the outputs of two Extended Kalman adaptive filters that simultaneously adapt using the same white Gaussian inputs. The purpose of the combination is to obtain an EKF adaptive filter with fast convergence and small steady-state mean-square deviation (MSD) for OFDM. The linear combination studied is a generalization of the convex combination, in which the combination factor λ(n) is restricted to the interval (0,1). The viewpoint is taken that each of the two filters produces dependent estimates of the unknown channel. Thus, there exists a sequence of optimal combining coefficients which minimizes the mean-square error (MSE). First, the optimal unrealizable combiner is studied and provides the best possible performance for this class. Then two new schemes are proposed for practical applications. The mean-square performances are analyzed and validated by MATLAB simulations. With proper design, the two practical schemes yield an overall MSD that is usually less than the MSDs of either filter.

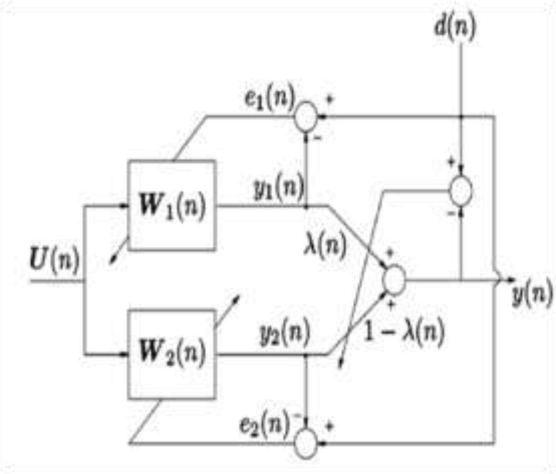

Figure 3: Proposed Adaptive Filter

Figure above is proposed design and the in [9], where adaptive filter uses a larger step size than adaptive filter. The key to this scheme is the selection of the scalar mixing parameter for combining the two filter outputs. The mixing parameter is defined in [7] as a sigmoid function whose free parameter is adaptively optimized using a stochastic gradient search which minimizes the quadratic error of the overall filter. The steady-state performance of this adaptive scheme has been recently studied in [8]. The convex combination performed as well as the best of its components in the MSE sense. These results indicate that a combination of adaptive filters can lead to fast convergence rates *and* good steady-state performance, an attribute that is usually obtained only in variable step-size algorithms. Thus, there is great interest in learning more about the properties of such adaptive structures. This approach used LMS adaptive filter we have used the approach for Extended Kalman Filter.

3. RESULTS

1. LMS order 32 IIR filter

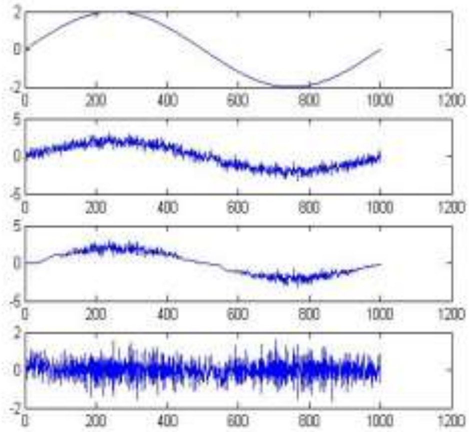

Figure 4: LMS filter (i) the signal
(ii) the noisy signal
(iii) the filtered signal
(iv) the noisy signal

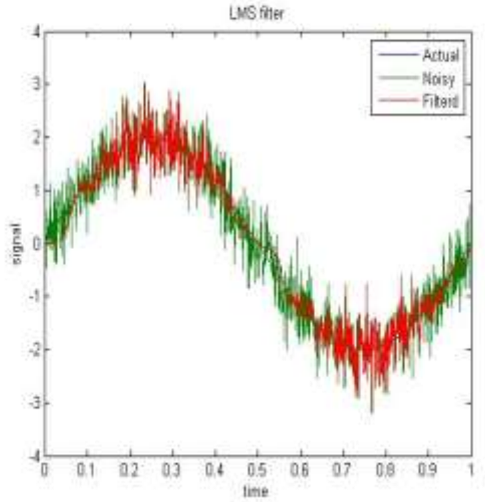

Figure 5: LMS filter observed result

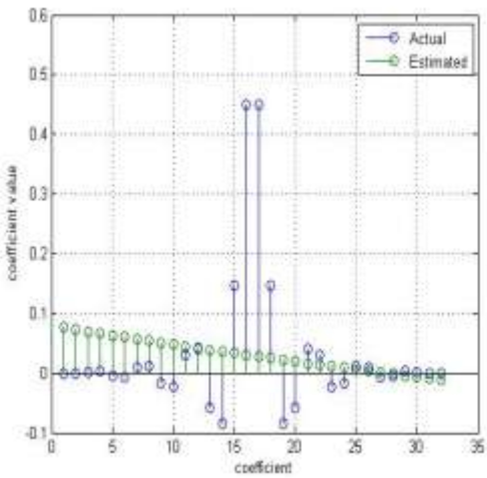

Figure 6: Impulse Response of LMS

2. RLS order 32 filter

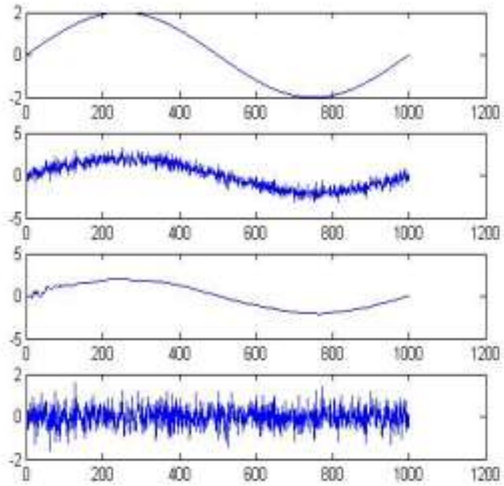

Figure 7 RLS filter (i) the signal
(ii) the noisy signal
(iii) the filtered signal
(iv) the noisy signal

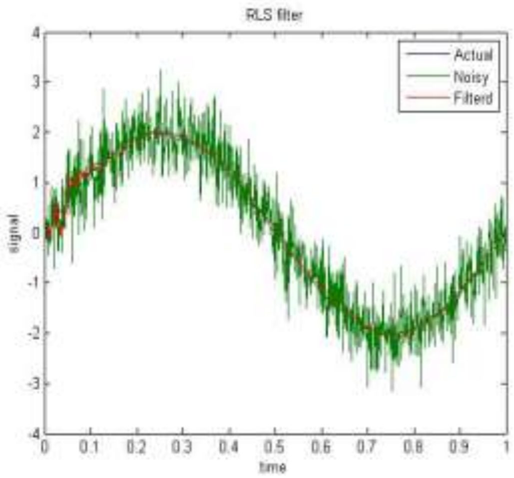

Figure 8: RLS Filter Observed Result

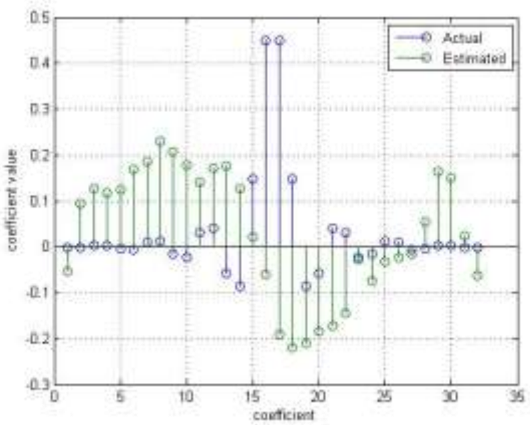

Figure 9: Impulse Response of LMS

3. Proposed Design of EKF

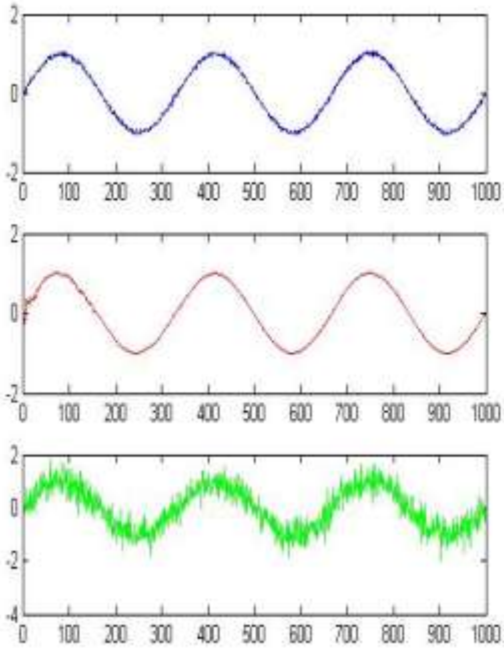

Figure 10: Proposed Kalman filter
(i) filtered signal
(ii) Original signal
(iii) Noisy signal

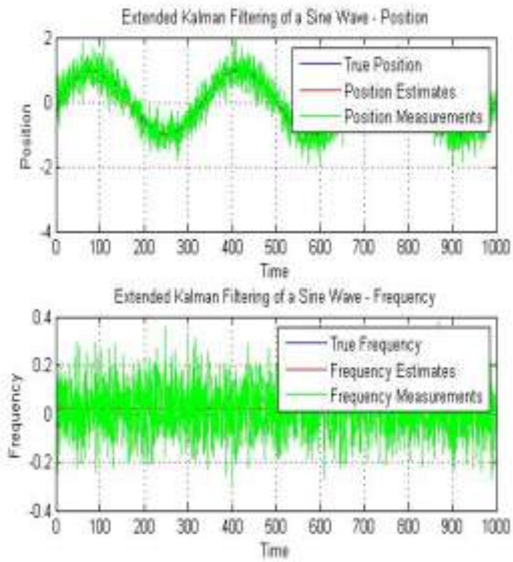

Figure 11: Proposed Kalman filter relative results

4. CONCLUSION

Fast time varying channels find many applications in military applications such as guided missiles and even in satellite launch vehicles. In this paper we were able to effectively mathematically model of new design of Extended Kalman Filter & reduce the white noise in non linier system. The paper functions mainly in the time domain and this allows us to implement the design of ref [9] increase SNR. The estimation is performed using the EKF and equalization is simplified using the QR equalizer. The EKF is able to track the parameters efficiently while the QR equalizer helps mitigate the ICI effectively. Thus, in this paper we have effectively implemented a complete MIMO – OFDM system model with an effective channel estimation adaptive filter.

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