

1/f BASEBAND NOISE SUPPRESSION IN OFDM USING KALMAN FILTER

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As the technology is advances the reduced size of hardware gives rise to an additive 1/f baseband noise. This additive 1/f noise is a system noise generated due to miniaturization of hardware and affects the lower frequencies. Though 1/f noise does not show much effect in wide band channels because of its nature to affect only certain frequencies, 1/f noise becomes a prominent in OFDM communication systems where narrow band channels are used. In this thesis, I study the effects of 1/f noise on the OFDM systems and implement algorithms for estimation and suppression of the noise using Kalman filter. Suppression of the noise is achieved by subtracting the estimated noise from the received noise. I show that the performance of the system is considerably improved by applying the 1/f noise suppression.

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CHAPTER 1

INTRODUCTION

1.1 Motivation

The growing demand for smarter, smaller, low power consuming devices with considerably good quality of service has given rise to development of more efficient devices and many techniques to improve these devices. All these devices are exemplified by various resources such as size, power, spectrum and other consumer needs. These characteristics are the reason for the constant development in smaller devices whose size is reducing considerably depending on consumer needs and also not compromising efficiency and quality of service.

1.2 Problem Statement

The goal is to improve quality of service expected by consumers by minimizing additional $1/f$ noise introduced in the system due to miniaturization of hardware. Miniaturization of hardware to increase speed and packing density has led to considerable reduction of size of transistors whose metal oxide gate has become even smaller; this led to introduction of an additional noise called flicker noise or $1/f$ baseband noise. $1/f$ noise is common in baseband analog front ends (AFE) utilizing direct-conversion RF, which are commonly used in orthogonal frequency division multiplexing (OFDM) transceivers. For a wide-band system introduction of $1/f$ noise around the DC is not an issue as it will only take up a small portion, but in transmission schemes such as OFDMA an user is allocated with a small portion of DC and having $1/f$ noise effect it becomes an issue. Thus, it is very essential to study the effect of $1/f$ noise on overall system. I use the noise model in [10] and implement it using Kalman filter to estimate the $1/f$ noise and then suppress the noise by subtracting it from the received signal.

1.3 Thesis Overview and Contribution

To achieve the goal, that is to improve the quality of communication between two digital devices by minimizing the noise caused due to miniaturization of hardware, we need a system which can estimate the noise based on data from previous communication attempts and also helps in minimizing or correcting the noise. Therefore, a Kalman filter is used in the receiver device to estimate the noise and lead to minimizing techniques which will be discussed in detail in later chapters.

1.4 Organization of the Thesis

The thesis starts with an introduction to the OFDM system in Chapter 2 and then discussing Kalman filtering in Chapter 3. Chapter 4 describes the problem definition and the system model used to acquire the goal of the thesis. The steps followed and simulation results are presented in Chapter 5. Chapter 6 discusses about the conclusions and future work.

CHAPTER 2

OFDM SYSTEM

2.1 Introduction

Initial work on orthogonal frequency division multiplexing (OFDM) was done in 60s and 70s. OFDM is a method of encoding data into different carriers on different frequencies [1]. As the name suggests OFDM depends on orthogonal principle, it uses subcarriers that are orthogonal to each other. The use of orthogonal subcarriers avoid crosstalk between co-channels and also eliminate the need for inter carrier guard bands. This simplifies the design of both transmitter and receiver.

OFDM is a digital multicarrier transmission which uses a large number of closely spaced orthogonal subcarriers and is suited for frequency selective channels and high data rates. OFDM transmission transforms frequency selective wide-band channels into a group of non-selective narrow band channels, which make it more useful against large delay spreads [2].

2.2 OFDM Principle

OFDM is a special form of multi carrier modulation (MCM) with densely spaced sub carriers with overlapping spectra, thus allowing for multiple-access. MCM is the principle of transmitting data by dividing the stream into several bit streams, each of which has a much lower bit rate, and by using these sub-streams to modulate several carriers [1]. In early developments of OFDM for large number of sub channels, arrays of sinusoidal generators and coherent demodulators were used, but this was both complex and expensive process. After a few years of development discrete Fourier transforms were applied to the transmission system as a part of modulation and demodulation process. Use of Fourier transforms helped in complete digital

implementation of the system [1].

To generate OFDM successfully the relationship between all the carriers must be carefully controlled to maintain the orthogonality of the carriers. For this reason, OFDM is generated by firstly choosing the spectrum required, based on the input data, and modulation scheme used. Each carrier to be produced is assigned some data to transmit. The required amplitude and phase of the carrier is then calculated based on the modulation scheme (typically differential BPSK, QPSK, or QAM).

Orthogonality plays a very important role in OFDM transmission. In OFDM, carriers can be arranged in such a way that the sidebands of individual carriers overlap and the signals can still be received without carrier interference, to achieve all carriers should be orthogonal to each other [1]. Mathematically the relation can be given by

$$\int_a^b \varphi_m(t)\varphi_n^*(t)dt = 0 \quad \text{where } m \neq n \quad (2.2.1)$$

The required spectrum is then converted back to its time domain signal using an inverse Fourier transform. In most applications, an inverse fast Fourier transform (IFFT) is used. The IFFT performs the transformation very efficiently, and provides a simple way of ensuring the carrier signals produced are orthogonal.

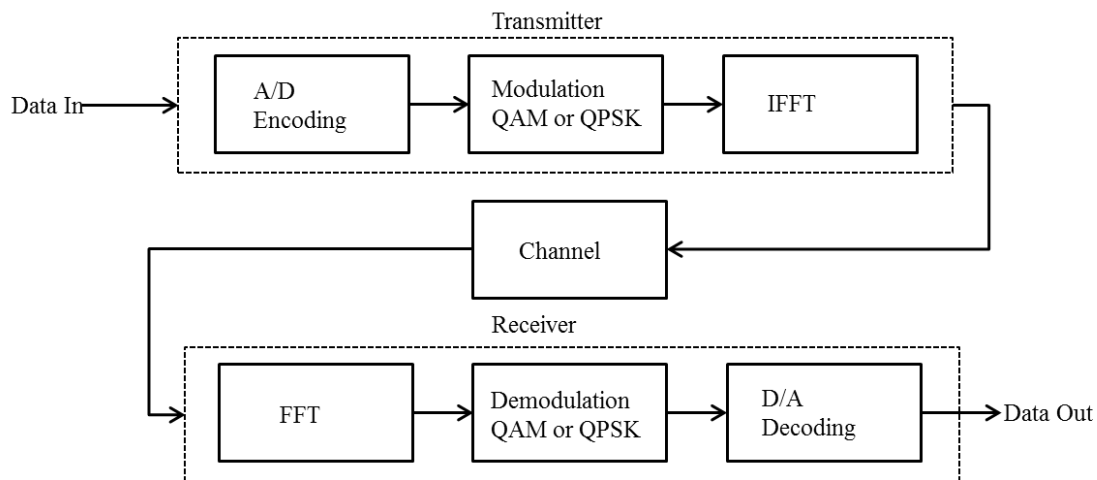


Fig 2.1 Basic block diagram of an OFDM system.

The IFFT performs the reverse process, transforming a spectrum (amplitude and phase of each component) into a time domain signal. An IFFT converts a number of complex data points, of length, which is a power of 2, into the time domain signal of the same number of points using the formula.

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{-i\omega x} d\omega \quad (2.2.2)$$

For a digital system an inverse discrete Fourier transform (IDFT) is used, which is given by

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{j\frac{2\pi}{N}kn}, 1 \leq n \leq N \quad (2.2.3)$$

Each data point in frequency spectrum used for an FFT or IFFT is called a bin. The orthogonal carriers required for the OFDM signal can be easily generated by setting the amplitude and phase of each bin, then performing the IFFT. Since each bin of an IFFT corresponds to the amplitude and phase of a set of orthogonal sinusoids, the reverse process guarantees that the carriers generated are orthogonal.

The fast Fourier transform (FFT) transforms a cyclic time domain signal into its equivalent frequency spectrum. This is done by finding the equivalent waveform, generated by a sum of orthogonal sinusoidal components. The amplitude and phase of the sinusoidal components represent the frequency spectrum of the time domain signal. This is done using the formula

$$F(\omega) = \int_{-\infty}^{\infty} f(x) e^{-j\omega x} dx \quad (2.2.4)$$

For a digital system a discrete Fourier transform (IDFT) is used, which is given by

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j\frac{2\pi}{N}kn}, 1 \leq k \leq N \quad (2.2.5)$$

The signal generated is a base band, thus the signal is filtered, then stepped up in frequency before transmitting the signal. OFDM time domain waveforms are chosen such that mutual

orthogonality is ensured even though sub-carrier spectra may overlap. Typically QAM or Differential Quadrature Phase Shift Keying (DQPSK) modulation schemes are applied to the individual sub carriers. To prevent ISI, the individual blocks are separated by guard intervals wherein the blocks are periodically extended.

2.3 OFDM Transmission

Quadrature amplitude modulation (QAM) and quadrature phase-shift keying (QPSK) are the basic modulation schemes widely used in OFDM. QAM is also known as band width conservation scheme, as it allows the modulated signals to occupy the same transmission band width at the receiver output. The QAM transmitter consists of two separate balanced modulators, which are supplied, with two carrier waves of the same frequency but differing in phase by 90°. The output of the two balanced modulators are added in the adder and transmitted. The transmitted signal is thus given by

$$s(t) = A(t) \cos(2\pi f_0 t) + B(t) \sin(2\pi f_0 t) \quad (2.3.1)$$

where $A(t)$ and $B(t)$ are modulating signals and f_0 is the carrier frequency. Hence the transmitted signal consists of an in-phase component and a quadrature phase component [3].

In QPSK the data stream is split into an in-phase component and a quadrature component, these split streams are modulated separately using two orthogonal basis functions. Then these modulated streams are superimposed for transmission. The QPSK constellation can be given by

$$s(t) = \sqrt{\frac{2E}{T}} \cos(2\pi f_c t + (2n - 1)\frac{\pi}{4}) \quad (2.3.2)$$

where f_c is the carrier frequency. The basis functions are given by

$$\phi_1(t) = \sqrt{\frac{2}{T}} \cos(2\pi f_c t) \quad (2.3.3)$$

$$\phi_2(t) = \sqrt{\frac{2}{T}} \sin(2\pi f_c t) \quad (2.3.4)$$

This modulation uses two modulating sinusoidal signal [5]. Due to the offset, the phase shift in QPSK signal is $\pi/2$.

The symbols generated after modulation are then passed through IFFT block to be converted to time domain signals. The IFFT output is the summation of all N sinusoids. Thus, the IFFT block provides a simple way to modulate data onto N orthogonal sub carriers. The block of N output samples from the IFFT make up a single OFDM symbol. The length of the OFDM symbol is NT where T is the IFFT input symbol period.

One of the most important properties of an OFDM system is its robustness against multipath delay spread. This is achieved by adding a guard band or intervals between the transmitted symbols to increase the symbol period, which will help in reduction of inter symbol interference. The most effective guard period to use is a cyclic extension of the symbol, where each OFDM symbol is preceded by the part of symbol itself. If the guard interval is longer than the channel impulse response or the multipath delay then the inter symbol interference can be eliminated [1].

At OFDM receiver the symbols are first converted to frequency domain by applying a fast Fourier transform (FFT). Ideally, the FFT output will be the original symbols that were sent to the IFFT at the transmitter. When plotted in the complex plane, the FFT output samples will form a constellation, such as 16-QAM. However, there is no notion of a constellation for the time-domain signal. When plotted on the complex plane, the time-domain signal forms a scatter

plot with no regular shape. Thus, any receiver processing signals using the concept of constellations must do processing in frequency domain.

2.4 Transmission Channels

The transmitted signals are electromagnetic waves which travel from transmitter to receiver. Along the way the wave encounters a wide range of different environments. Channel models represent the attempt to model these different environments. One of the basic non fading channels used in simulations is AWGN channel. In this channel we consider that the transmitted signal is equal to received signal with a small amount of white Gaussian noise added to it. It can be represented as

$$S(t) = s(t) + n(t) \quad (2.4.1)$$

where $s(t)$ is the transmitted signal and $n(t)$ is the white Gaussian noise.

Multipath channel is based on the fact that electromagnetic waves can take any path or can be reflected by multiple surfaces before reaching the receiver and many versions of the same signal can be received at the receiver at different times. Therefore, the receiver sums up the received signals. In this kind of channel the concept of inter symbol interference comes into effect.

Fading channels are the channels that are explained by mathematical models based on wireless data exchange in physical environment. The basic scenarios considered while studying a fading channel are the change in environment even though the transmitter and receiver are fixed and the transmitter and receiver are mobile in a static environment .

CHAPTER 3

KALMAN FILTER

3.1 Basic Concept

Kalman filter was developed by Rudolph E. Kalman in 1960. The Kalman filter is a recursive predictive filter that is based on the use of state space techniques and recursive algorithms, which also gives solution to the discrete-data filtering problem [5][6]. Kalman filter consists of two steps, prediction and correction. Prediction step follows a dynamic model whereas the correction step follows an observation model. As corrections are made to predictions based on observations that error covariance of the estimator is minimized.

The prediction and correction steps are repeated for each time step. Therefore the Kalman filter is called a recursive filter. The basic components of Kalman filter are state vector, the dynamic model and the observation model.

The state vector describes the state of dynamic system and represents its degree of freedom. The variables in state vector cannot be inferred directly but can be inferred from the measurable values. The dynamic model describes the transformation of state vector over a period of time. It can be represented by a system of differential equations. The observation model gives the relationship between state and measurements. In linear system the measurements can be described by a system of linear equations, which depend on the state variables [5].

3.2 Kalman Filter

The Kalman filter addresses the general problem to find state $x \in Q^n$ of the discrete time controlled process that is given by differential equation

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (2.2.1)$$

With a measurement $z \in Q^m$ that is

$$z_k = Hx_k + v_k \quad (2.2.2)$$

where the random variables w_k and v_k represent the process and measurement noise respectively and are assumed to be independent, white and with normal probability distribution [6].

The following set of variables are given

- the noise characterization, the initial conditions,
- set of controls
- set of measurements.

In the prediction step an a posteriori state estimate is computed as a linear combination of an a priori estimate and a weighted difference between an actual measurement and a measurement prediction. In correction step the Kalman gain is calculated, estimate of is updated with measurement and error covariance is also updated.

Steps in the Kalman filter algorithm:

1. Initial Conditions:

Initial estimates of \hat{x}_{k-1} and P_{k-1} are calculated.

2. Prediction Step

- Project the state ahead

$$\hat{x}_k^- = A\hat{x}_{k-1}^- + B u_{k-1} \quad (2.2.3)$$

- Project the error covariance ahead

$$P_k^- = AP_{k-1}A^T + Q \quad (2.2.4)$$

3. Correction Step

- Compute the Kalman gain

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \quad (2.2.5)$$

- Update the estimate with measurement z_k

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \quad (2.2.6)$$

- Update the error covariance

$$P_k = (I - K_k H)P_k^- \quad (2.2.7)$$

4. Let $k = k+1$ and repeat from step 2.

The above stated steps are to implement the Kalman filter [6]. However, if the estimation problem is not stated clearly, some numerical problems like covariance becoming indefinite or losing the symmetry of covariance may occur. To overcome these problems a square root method is used where square root of covariance is used instead of direct value this assures the symmetry of covariance matrix. One such method of implementation is the unscented Kalman filter.

The Kalman filter is mostly used for linear applications, but as we know most of the real time systems are nonlinear to solve this we can use the extended version of Kalman filter known as extended Kalman filter (EKF) [7].

3.3 Extended Kalman Filter

As described previously Kalman filter addresses the estimation problems of a linear system. But if a system is nonlinear we need a filter that linearizes about the current mean and covariance, such a filter is called an extended Kalman filter or EKF.

Extended Kalman filter addresses the problem to find state $x \in Q^n$ of a process which is governed by the non-linear stochastic difference equation [6]

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \quad (2.3.1)$$

With the measurement $z \in Q^m$ that is

$$z_k = h(x_k, v_k) \quad (2.3.2)$$

where the random variables w_k and v_k represent the process and measurement noise respectively and are assumed to be independent, white and with normal probability distribution. The nonlinear function f relates the state at previous time step $k-1$ to the current time step k . The nonlinear function h relates the state to the measurement [6].

The steps involved in extended Kalman filter operation are

1. Initial Conditions:

Initial estimates of \hat{x}_{k-1} and P_{k-1} are calculated.

2. Prediction Step

- Project the state ahead

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, 0) \quad (2.3.3)$$

- Project the error covariance ahead

$$P_k^- = A_k P_{k-1} A_k^T + W_k Q_{k-1} W_k^T \quad (2.3.4)$$

3. Correction Step

- Compute the Kalman gain

$$K_k = P_k^- H^T (H P_k^- H^T + V_k R V_k^T)^{-1} \quad (2.3.5)$$

- Update the estimate with measurement z_k

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - h(\hat{x}_k^-, 0)) \quad (2.3.6)$$

- Update the error covariance

$$P_k = (I - K_k H) P_k^- \quad (2.3.7)$$

4. Let $k = k+1$ and repeat from step 2.

An important feature of EKF is the Jacobian H_k in the equation of Kalman gain helps to propagate only the relevant component of the measurement [6].

CHAPTER 4

PROBLEM DEFINITION AND SYSTEM MODEL

4.1 Problem Statement

Advances in very-large-scale integration technology has led to miniaturization of hardware in digital devices reducing the size of transistors on chips to a considerable amount. One effect of this downsizing is introduction of 1/f base band noise.

As the metal oxide gate on transistors is decreased to increase the speed and packing density the flicker noise or 1/f base band noise increases. This noise is additive in nature and due to its spectral shape mainly effects the frequencies around direct conversion.[8] Such baseband noise is common in Analog Frond Ends using direct conversion RF (DCR) [9], used by OFDMA transceivers.

We estimate 1/f noise using noise model in [10] and suppress 1/f noise by subtracting the estimated 1/f noise from the received signal. The estimation of 1/f noise is done using Kalman filter, which computes new estimate for every received signal [11].

4.2 System Model

In order to estimate 1/f noise we follow the noise model given in [10]. This model is developed using N+1 first-order differential equations, where N is a model parameter. The 1/f noise model is given by

$$\dot{y}_{2N}(t) = y_{2N}(t) - y_{2N}(0) + 2 \left[v(t) - \phi(t) - 2 \sum_{k=1}^N y_{2k}(t) \right] \quad (3.2.1)$$

$$\begin{aligned} \dot{y}_{2N-2}(t) = & y_{2N-2}(t) - y_{2N-2}(0) - 4y_{2N}(t) \\ & + 4 \left[v(t) - \phi(t) - 2 \sum_{k=1}^{N-1} y_{2k}(t) \right] \end{aligned} \quad (3.2.2)$$

$$\begin{aligned} \dot{y}_{2N-4}(t) = & y_{2N-4}(t) - y_{2N-4}(0) - 4y_{2N}(t) - 8y_{2N-2}(t) \\ & + 6 \left[v(t) - \phi(t) - 2 \sum_{k=1}^{N-2} y_{2k}(t) \right] \end{aligned} \quad (3.2.3)$$

$$\begin{aligned} \dot{y}_2(t) = & y_2(t) - y_2(0) - 4 \sum_{m=1}^{N-1} m y_{2(N-m+1)}(t) \\ & + 2N[v(t) - \phi_n(t) - 2y_2(t)] \end{aligned} \quad (3.2.4)$$

$$\begin{aligned} \dot{\phi}(t) = & -(2N + 1)\phi(t) - \phi(0) - 4 \sum_{m=1}^N m y_{2(N-m+1)}(t) \\ & + 2(N + 1)v(t) \end{aligned} \quad (3.2.5)$$

where $v(t)$ is a white Gaussian noise and $\Phi(t)$ is the approximated 1/f Gaussian process.

Therefore, Nth approximation to the 1/f noise process is an output of a Markovian system of N+1

linear stochastic differential equations [11] [12]. The above equations can also be written as

$$\dot{x}(t) = Ax(t) + Bv(t) \quad (3.2.6)$$

Where the matrices A and B are given by

$$A = \begin{bmatrix} -3 & -4 & -4 & \cdot & \cdot & \cdot & -4 & -2 \\ -4 & -7 & -8 & \cdot & \cdot & \cdot & -8 & -4 \\ -4 & -8 & -11 & \cdot & \cdot & \cdot & -12 & -6 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ -4 & -8 & -12 & \cdot & \cdot & \cdot & -4N - 1 & -2N \\ -4 & -8 & -12 & \cdot & \cdot & \cdot & -4N & -2N - 1 \end{bmatrix} \quad (3.2.7)$$

and

$$B = \begin{bmatrix} 2 \\ 4 \\ \cdot \\ \cdot \\ 2N \\ 2(N+1) \end{bmatrix} \quad (3.2.8)$$

Respectively and the state vector $x(t)$ is defined as

$$x(t) = \begin{bmatrix} y_{2N}(t) \\ y_{2N-2}(t) \\ \cdot \\ \cdot \\ y_2(t) \\ \phi(t) \end{bmatrix} \quad (3.2.9)$$

Equation 3.2.6 describes the model for 1/f noise for a continuous time where as a model for discrete time has to be obtained. In [13] the author derived a discrete time model from a continuous one. It is defined as follows, let

$$C = \begin{bmatrix} -A & QBB^T \\ 0 & A^T \end{bmatrix} \quad (3.2.10)$$

where Q is used to control 1/f noise intensity. Let

$$e^{C\Delta_t} = \begin{bmatrix} A_2 & B_2 \\ 0 & A_3 \end{bmatrix} \quad (3.2.11)$$

where Δ_t is time sample between two samples of discrete process. Now using equations 3.2.7 and 3.2.11 we can define

$$Q_d = A_3^T B_2 \quad (3.2.12)$$

$$\Phi = e^{A\Delta_t} \quad (3.2.13)$$

From the above two equations the discrete model is given by

$$\xi_{k+1} = \Phi \xi_k + w_k \quad (3.2.14)$$

where w_k is an independent Gaussian vector process with covariance matrix Q_d . ξ_k is the desired 1/f sampled process [11]. The 1/f noise spectral density can be given by

$$S_{\phi\phi}(f) = \frac{Q}{2\pi|f|} \quad (3.2.15)$$

The complex envelop of an OFDM signal can be expressed as

$$s(t) = (h(t) \otimes \sum a_m e^{j2\pi\frac{m}{T}t}) \quad (3.2.16)$$

where data a_m modulated the sinusoid at frequency m/T during symbol time T and $h(t)$ denotes the channel impulse response [11]. The received complex signal r_k at the transceiver's baseband is given by the equation

$$r_k = s_k + v_k + \phi_{I,k} + j\phi_{Q,k} \quad (3.2.17)$$

where v_k is a complex additive Gaussian thermal noise process. Variance of this noise is defined such that it has N_0 variance for every subcarrier in the frequency domain.

4.3 Noise Estimation Scheme

Using the discrete mode l in equation 3.2.14 Kalman filter is applied to estimate the noise processes $\phi_{I,k}$ and $\phi_{Q,k}$. The observation mode l is given by equation 3.2.17. The estimation of $\phi_{I,k}$ is done on real part of r_k whereas the estimation of $\phi_{Q,k}$ is done on the imaginary part of the received signal. The estimation equation that shall be used for recursive computation using Kalman filter is given by [11]

$$\hat{\phi}_{k|k} = G \hat{\xi}_{k|k} \quad (3.3.1)$$

where G is given by

$$G^T = \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \\ 1 \end{bmatrix} \quad (3.3.2)$$

The first step is the prediction step

$$\hat{\xi}_{k|k-1} = A\hat{\xi}_{k-1|k-1} \quad (3.3.3)$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q_d \quad (3.3.4)$$

where a priori predicted estimate state is given by equation 3.3.3 and estimate covariance is given by equation 3.3.4. The update step is given by following equations [11]

$$\bar{r}_k = \tilde{r}_k - G\hat{\xi}_{k|k-1} \quad (3.3.5)$$

$$S_k = GP_{k|k-1}A^T + V \quad (3.3.6)$$

$$K_k = P_{k|k-1}G^T S_k^{-1} \quad (3.3.7)$$

$$\hat{\xi}_{k|k} = \hat{\xi}_{k|k-1} + K_k\bar{r}_k \quad (3.3.8)$$

$$P_{k|k} = (I - K_kG)P_{k|k-1} \quad (3.3.9)$$

where the observation \tilde{r}_k can be either real or imaginary. V is the variance of $s_k + v_k$. S_k is the innovation covariance, K_k is the optimal Kalman gain. Equations 3.3.8 and 3.3.9 give the updates state estimate and covariance [11]. The initial conditions are taken as

$$\hat{\xi}_{0|0} = 0, P_{0|0} = 0 \quad (3.3.10)$$

The variance V can be estimated either by estimating the power of received samples at the output high pass filter with a low frequency cutoff at $1/f$ noise corner frequency or by subtracting the estimated $1/f$ noise power from the total of the received samples [14].

In [11] the author has worked on elimination of $1/f$ baseband noise in an OFDM system using an environment closer to real time environment and also taking into consideration relative

motion between transmitter and receiver. In present thesis I have simulated similar conditions for a transmission using Raleigh fading channel.

CHAPTER 5

SIMULATION RESULTS

The steps followed in this thesis to estimate and suppress 1/f noise are:

- Estimate the 1/f noise in the received signal.
- Subtract the estimated noise from the received signal.
- Calculate errors with suppression and without suppression of baseband noise and check for better performance of the system.

The OFDM system was simulated using one transmitter and receiver antenna and both fading and non-fading channels. The additive 1/f baseband noise is generated using the equation 3.2.14 with model order of $N=100$. 1/f baseband noise can also be generated using an exact model given in [13][11]. This is given by equation

$$\phi_n = \sum_{k=1}^n -a_k \phi_{n-k} + u_n \quad (4.1.1)$$

where coefficient a_k is given by

$$a_0 = 1, a_k = (k - 1 - \frac{1}{2}) \frac{a_{k-1}}{a_k} \quad (4.1.2)$$

The runtime for the exact model is longer than the approximated model, since in exact model generation of each new sample involves all the previous samples. This dependence helps in better estimation of characteristics of 1/f noise. The SNR is defined as

$$SNR = \frac{E_s}{N_0} \quad (4.1.3)$$

where E_s is the subcarrier means energy and N_0 is the white thermal baseband noise energy for single subcarrier [11]. The following figure gives curves of block error rate (BLER) where 1/f baseband noise is not present, two curves of BLER in the presence of 1/f baseband noise one generated using equation 3.2.14 and other using equation 4.1.1 and the curve after suppression of 1/f baseband noise.

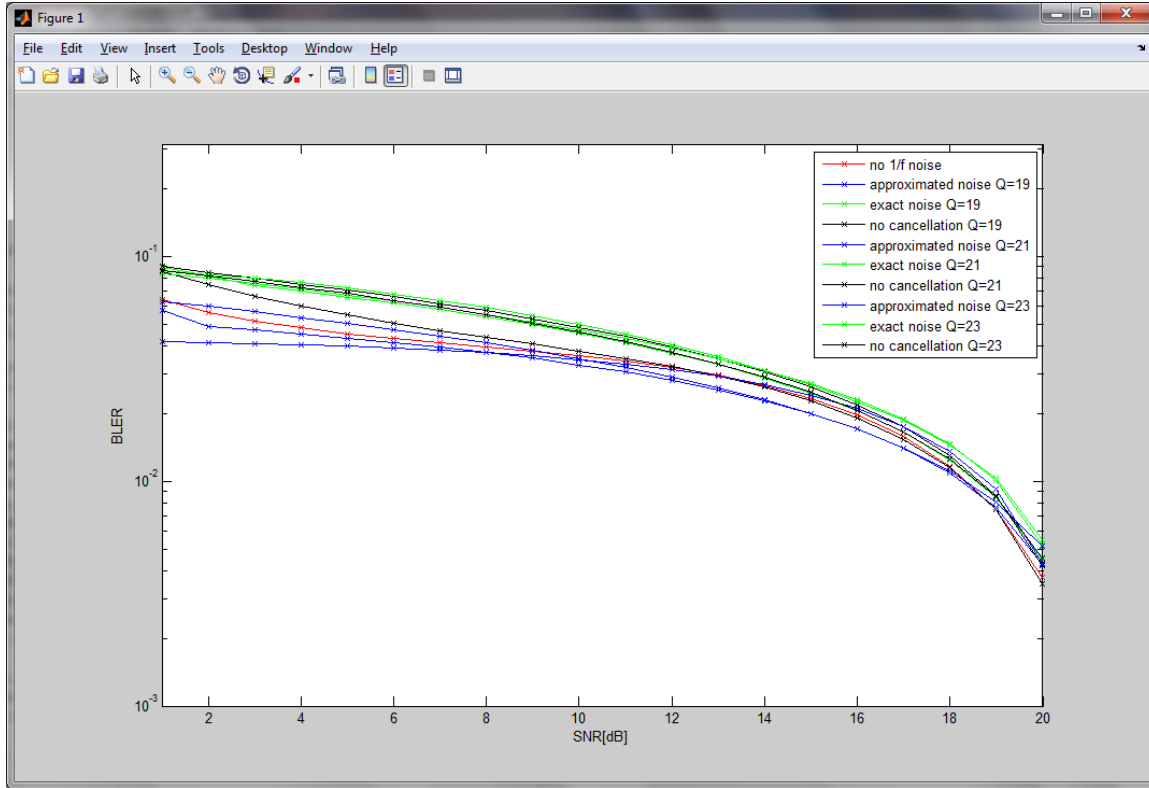


Fig. 5.1 Simulation depicts relation between BLER and SNR the green curves depict the estimation done using exact model, blue curves depict estimation done using approximated model and the black curves depict system with no 1/f noise cancellation. These were done using Q as 19dB, 21dB and 23dB.

To get a better understanding of estimation process, the real part of received signal, the real part of 1/f baseband noise and the estimated part of 1/f baseband noise are presented in the next simulation. Considering $s_k + v_k$ to be the desired signal, normalized least mean square error (NMSE) [11] before suppression is given by

$$NMSE = 10 \log_{10} \frac{\sum |\phi_{I,k} + j\phi_{Q,k}|^2}{\sum |s_k + v_k|^2} \quad (4.1.4)$$

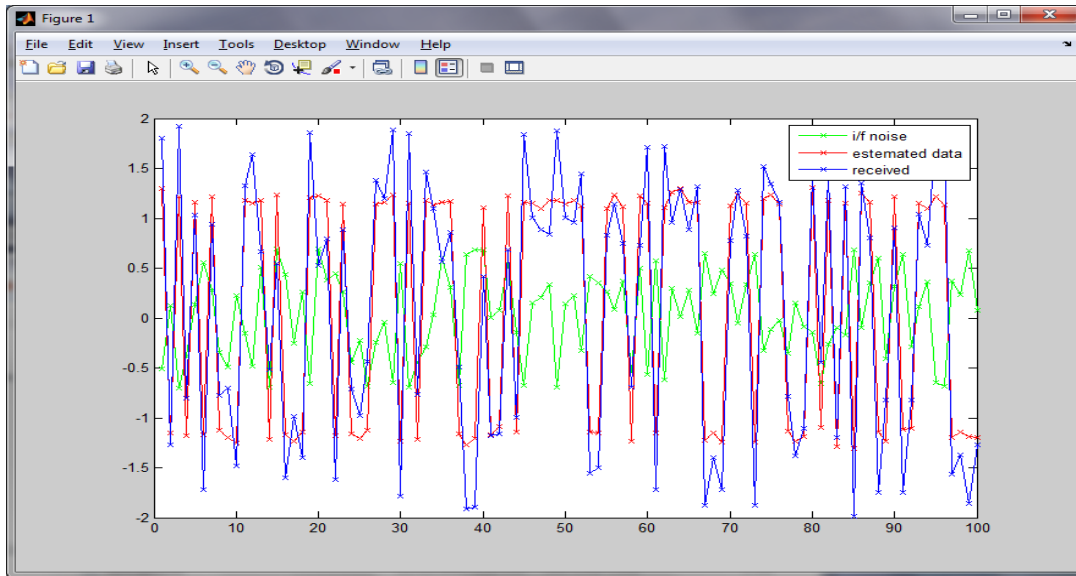


Fig. 5.2 Simulation depicting the time domain phase noise estimation: the blue signal is the received signal, the green signal is the 1/f noise, and the red signal is the estimation of 1/f noise from the received signal.

The gains resulting in suppression of 1/f baseband noise can be represented by plotting remaining 1/f baseband noise and the processing gain. This simulation is shown in the following plot

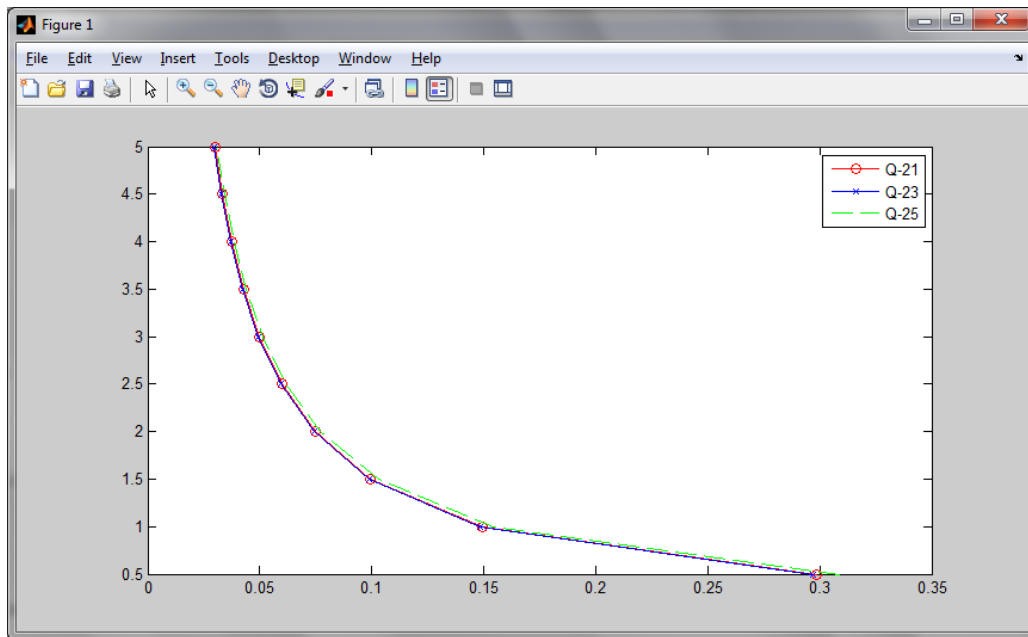


Fig. 5.3 Simulation depicting the processing gain vs. the remaining 1/f baseband noise levels after suppression.

The processing gain is higher for higher Q, this is because the total level of suppressed noise is higher for higher Q even when the normalized remaining noise is the same. All the above simulations were performed taking $N = 5$. Now to estimate the proper order to get good estimation simulation for different N is shown below.

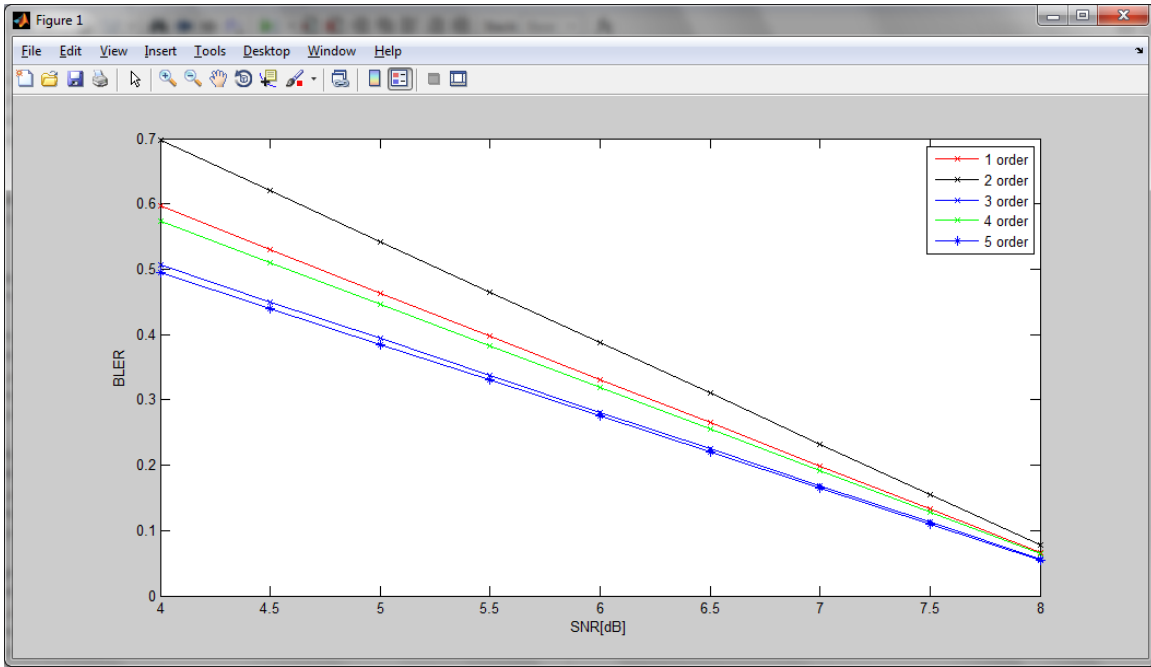


Fig. 5.4 Simulation depicting BLER vs. SNR for different approximation orders. The noise level was set at $Q = 19$ dB.

It can be seen that an approximation of order $N=5$ is enough to achieve acceptable results. As the $1/f$ noise is mainly concentrated in the corner frequencies the estimation can be performed after the received signal is passed through a low pass filter. This would save computation time.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

As the technology is advancing and utilizing smaller transistors $1/f$ baseband noise is becoming a prominent issue. The effects of $1/f$ noise in an OFDM system were investigated and the performance of system after the suppression of $1/f$ noise was shown through a series of simulations which showed increase in processing gain of the system which can be used in design and implementation of systems.

In this thesis, a $1/f$ noise suppression algorithm was implemented using Kalman filter over an OFDM system using a non-fading awgn channel. Thus the Kalman filter is used in estimation of $1/f$ baseband noise during a communication and in improving the quality of communication by suppressing the noise using the estimate given by the filter.

This work can be further enhanced by implementing the system using other filters like particle filter. Moreover, estimation and suppression of other noises introduced during the communication can also be included to the $1/f$ baseband noise estimation.

REFERENCES

- [1] Matiae. D, *OFDM as a possible modulation technique for multimedia applications in the range of mm waves*, Introduction to OFDM, II edition, 1998.
- [2] M. Debbah, *Short introduction to OFDM*, White Paper, Mobile Communications Group, Institute Eurecom, February 2004.
- [3] http://en.wikipedia.org/wiki/Quadrature_amplitude_modulation
- [4] http://en.wikipedia.org/wiki/Phase-shift_keying
- [5] Rachel Kleinbauer, *Kalman Filtering Implementation with Matlab*, study report, University Stuttgart, Helsinki, November 2004
- [6] Greg Welch and Gary Bishop, *An Introduction to the Kalman Filter*, Technical Report, University of North Carolina at Chapel Hill Chapel Hill, NC, USA,1995.
- [7] D. Simon, *Kalman Filtering*, Embedded Systems Programming, vol. 14, no. 6, pp. 72-79, June 2001.
- [8] Chew, K.W. Yeo, K.S. Chu, S.-F.; , *Impact of technology scaling on the 1/f noise of thin and thick gate oxide deep submicron NMOS transistors*, Circuits, Devices and Systems Proceedings of the IEEE, vol.151, no.5, pp. 415- 421, 15 Oct. 2004
- [9] Won Namgoong, Meng T.H., *Direct-conversion RF receiver design*, Communications, Proceedings of the IEEE, vol.49, no.3, pp.518-529, Mar 2001
- [10] S. Landis, Z. Schuss, and B. Z. Bobrovsky, *The exit problem in a nonlinear system driven by 1/f noise: the delay locked loop*, SIAM J. Appl. Math., vol. 66, pp. 1188-1208, Apr. 2006
- [11] Landis S, Bobrovsky B. Z., *1/f Baseband Noise Suppression in OFDM Systems*, Communications, Proceedings of the IEEE, vol.59, no.4, pp.942-947, April 2011
- [12] Z. Schuss, *Theory and Applications of Stochastic Processes: An Analytical Approach*. Springer, 2010
- [13] Kasdin N.J., *Discrete simulation of colored noise and stochastic processes and 1/f α power law noise generation*, Proceedings of the IEEE, vol.83, no.5, pp.802-827, May 1995
- [14] Georgiadis A., *AC-coupling and 1/f noise effects on baseband OFDM signals*, Communications Proceedings of the IEEE, vol.54, no.10, pp.1806-1814, Oct. 2006