

IMM Based Kalman Filter for Channel Estimation in UWB OFDM Systems

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Abstract: Ultra-wide band (UWB) communication is one of the most promising technologies for high data rate wireless networks for short range applications. This paper proposes a blind channel estimation method namely IMM (Interactive Multiple Model) based Kalman algorithm for UWB OFDM systems. IMM based Kalman filter is proposed to estimate frequency selective time varying channel. In the proposed method, two Kalman filters are concurrently estimating channel parameters. The first Kalman filter, namely the Static Model Filter (SMF) gives an accurate result when the user is static while the second Kalman filter namely the Dynamic Model Filter (DMF) gives an accurate result when the receiver is in moving state. The static transition matrix in SMF is assumed as an Identity matrix where as in DMF, it is computed using Yule-Walker equations. The resultant filter estimate is computed as a weighted sum of individual filter estimates. The proposed method is compared with other existing channel estimation methods.

Keywords: Channel estimation, Kalman filter, UWB, Channel model, AR model

I. INTRODUCTION

Ultra wideband (UWB) is a fast emerging technology with uniquely attractive features inviting major advances in wireless communication, networking, radar, imaging and positioning systems [1][3]. OFDM has recently been applied in wireless communication due to its high data rate transmission capability with high bandwidth efficiency and robustness to multi-path delay. UWB OFDM called Multiband OFDM (MB OFDM), is a communication technique for the physical layer in the IEEE 802.15.3a standard which covers wideband communication in Wireless Personal Area Networks (WPANs) [2]. UWB signals with short duration of pulses provide unique advantage in short range application which includes easy penetration through obstacles, high precision ranging and low processing power.

The channel model for UWB communication is entirely different from narrowband wireless communication and many channel models have been proposed in literatures. In

practice OFDM systems operate over a dispersive channel and therefore a guard interval is usually inserted in the transmitted sequence. The guard interval may be of Cyclic Prefix (CP) of the data symbol or zeros and its length greater than the maximum delay spread of the channel. A combination of IFFT and CP at the transmitter with FFT at the receiver converts the frequency selective channel into parallel flat faded sub channels [9, 10]. A pilot based channel estimation technique using Kalman filter for OFDM communication has also been proposed [13]. However in this method, the state transition matrix in the Kalman filter is assumed as an identity matrix. Interacting Multiple Model (IMM) based Kalman algorithm is proposed for RADAR signal tracking. Evolution of fading channel parameters in time domain can be described by an Auto Regressive (AR) process [14]. Using an AR model, the parameters in the state transition matrix are derived. These parameters are computed from Jakes fading channel model using Yule walker equations [15].

The rest of the paper is organized as follows; Section II describes the UWB channel and System model for IEEE 802.15.3a WPANs with detailed specifications. In section III, a novel channel estimation scheme using Kalman filter is proposed. Section IV presents the extensive simulation results under various channel conditions to validate our method.

II. UWB CHANNEL AND SYSTEM MODEL

The most famous multipath UWB indoor channel models are tap-delay line Rayleigh fading model, Saleh-Valenzuela model [5] and Δ -K model. Recently Intel proposed a modified S-V model for UWB communication [7]. The arrival of multi-path components are modeled by using a statistically random process, it is based on a Poisson distribution. The multipath arrival of UWB signals are grouped into two categories, cluster arrival and ray arrival within a cluster the impulse response of the UWB channel can be written as[6],

$$h(t,\tau) = \sum_{l=0}^{L-1} \sum_{k=0}^{K-1} \alpha_{k,l} \delta(t-T_l - \tau_{k,l}) \quad (1)$$

Where $\alpha_{k,l}$ is the multipath gain coefficient of k^{th} ray related to l^{th} cluster. T_l is the delay or arrival time of the first path of l^{th} cluster. $\tau_{k,l}$ is the delay of k^{th} path within the l^{th}

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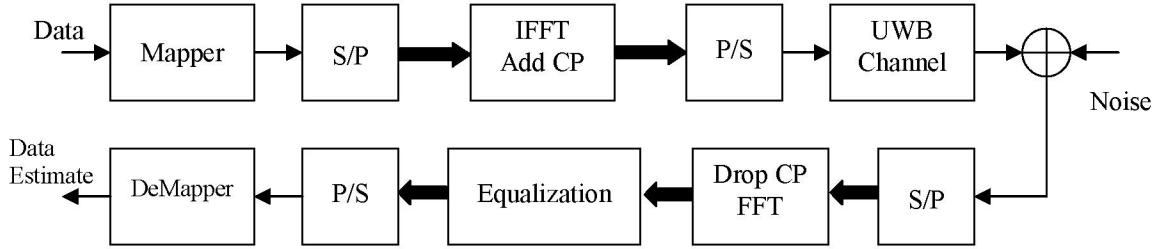


Fig. 1. Block Diagram of the System Model

cluster relative to T_l . X is the lognormal shadowing term. The ray arrival and cluster arrival distribution time are given by

$$p(T_l/T_{l-1}) = \Lambda \exp[-\Lambda(T_l - T_{l-1})] \quad l > 0 \quad (2)$$

$$p(\tau_k/\tau_{k-1}) = \lambda \exp[-\lambda(\tau_k - \tau_{k-1})] \quad k > 0 \quad (3)$$

The channel coefficients are the product of large scale and small scale fading components which are given by

$$\alpha_{k,l} = p_{k,l} \beta_{k,l} \quad (4)$$

$\beta_{k,l}$ is the amplitude of the UWB signal and it is based on a lognormal distribution. This is given as

$$20 \log 10(\beta_{k,l}) \sim \text{Normal}(\mu_{k,l}, \sigma_1^2 + \sigma_2^2) \quad (5)$$

Where σ_1 is the standard deviation of the cluster lognormal fading term. σ_2 is the standard deviation of the ray lognormal fading term. The behavior of averaged power delay profile is

$$E[\beta_{k,l}]^2 = \Omega_0 e^{-\frac{T_l}{\Gamma}} e^{-\frac{\tau_{k,l}}{\gamma}} \quad (6)$$

Where Γ and γ are the cluster and the ray decay factor. This reflects the exponential decay of each ray as well as decay of the total cluster power with respect to delay. X is the shadowing term and it is characterized by

$$20 \log 10(X) \sim \text{Normal}(0, \sigma^2) \quad (7)$$

σ is the standard deviation of lognormal shadowing term. In UWB OFDM systems, the entire UWB spectrum is divided in 14 subbands, each with a bandwidth of 528 MHz. The multipath resolution of the UWB OFDM channel model is different from other UWB channel models. The channel parameters are generated as per UWB channel model, passed through a low pass filter and a re-sampling circuit with respect to UWB OFDM symbol rate [4].

III. SYSTEM MODEL

The OFDM transmission model [8] considered in this paper is shown in Fig.1. The OFDM transmitter converts

input data into N parallel data sequences and they are modulated by the Inverse Fast Fourier Transform (IFFT) in base band and then converted into serial data. The Guard Interval (GI) in which zero is inserted between symbols to avoid InterSymbol Interference (ISI) caused by multipath fading. The complex base band signal is written as

$$r_{RF}(t) = \text{Re} \left\{ \sum_{k=0}^{N-1} r_k(t-kT_{sym}) e^{j2\pi f_k t} \right\} \quad (12)$$

Where $\text{Re}(\cdot)$ represents the real part of the complex variable. $r_k(t)$ is the complex base band signal of the k^{th} OFDM symbol and it is nonzero over the interval from 0 to T_{SYM} . N is the number of OFDM symbols. T_{SYM} is the symbol interval and f_k is the center frequency for the k^{th} band. All of the OFDM symbols $r_k(t)$ can be constructed using an IFFT with certain set of coefficients $x_n(i)$, where the coefficients are defined as either data, pilot or training symbols.

$$s_{OFDM}(t) = \sum_{i=-\infty}^{\infty} \sum_{n=-N_{ST}/2}^{N_{ST}/2} x_n(i) p_c(t-iT_{CP}) e^{j2\pi n \Delta f (t-iT_{CP})} \quad (13)$$

Where Δf and N_{ST} are defined as the subcarrier frequency spacing and the total number of subcarrier. T_{CP} and T_{GI} are the cyclic prefix duration and guard interval duration which are used in OFDM to mitigate the effects of multipath. $p_c(t)$ is a rectangular symbol pulse waveform defined as

$$p_c(t) = \begin{cases} 1, & 0 \leq t \leq T_{FFT} + T_{CP} \\ 0, & T_{FFT} + T_{CP} \leq t \leq T_{FFT} + T_{CP} + T_{GI} \end{cases} \quad (14)$$

The received signal of one user through UWB channel is written as

$$y(t) = \int_{-\infty}^{\infty} s_{OFDM}(t-\tau) \otimes h(\tau; t) d\tau + n(t)$$

$$y(t) = \sum_{i=-\infty}^{\infty} \sum_{n=-N_{ST}/2}^{N_{ST}/2} z_n(t) x_n(i) p_c(t-iT_{CP}) e^{j2\pi n \Delta f (t-iT_{CP})} + n(t) \quad (15)$$

Where $z_n(t)$ is the received complex envelop at the n^{th} subcarrier.

IV. INTERACTION MULTIPLE MODEL (IMM) ALGORITHM FOR CHANNEL ESTIMATION AND TRACKING

IMM based Kalman filtering algorithm is proposed to estimate and track the time varying frequency selective fading channel. A simple IMM based filter for channel tracking consists of two models namely the Static Model Filter (SMF) and the Dynamic Model Filter (DMF). A SMF provides a better estimate of the channel parameters when the receiver is static and a DMF gives a better estimate of the channel when the receiver is in moving state. The estimated channel parameters are combined based on model probabilities. The model probabilities are updated for each time based on residuals. The state transition matrix in the SMF is assumed as an Identity Matrix. For DMF, the state transition matrix and Noise covariance matrix parameters are derived using Yule walker equations from Jakes fading channel model. The block diagram of the proposed IMM based channel estimation filter is shown in Fig.2. The channel parameters are considered as state vector and the received signal parameters are considered the measurement vector.

The system equation is modeled as follows

$$X(t+1) = \Phi X(t) + n(t) \quad (16)$$

Where $X(t)$ is the state vector and Φ is the state transmission matrix which is different for the static and the dynamic model filter. $n(t)$ is the zero mean, white Gaussian noise with covariance Q . The measurement vector is modeled as

$$Z(t) = B(t) X(t) + u(t) \quad (17)$$

Where $B(t)$ is the measurement matrix of size $N \times N$ which is the estimate of transmitted signal vector and $u(t)$ is the zero mean white Gaussian measurement noise with covariance R_e . The steps involved in the Interacting Multiple Model algorithm are given below.

Step 1: interaction

Let X^i be the filtered state vector of the i^{th} filter and P^i

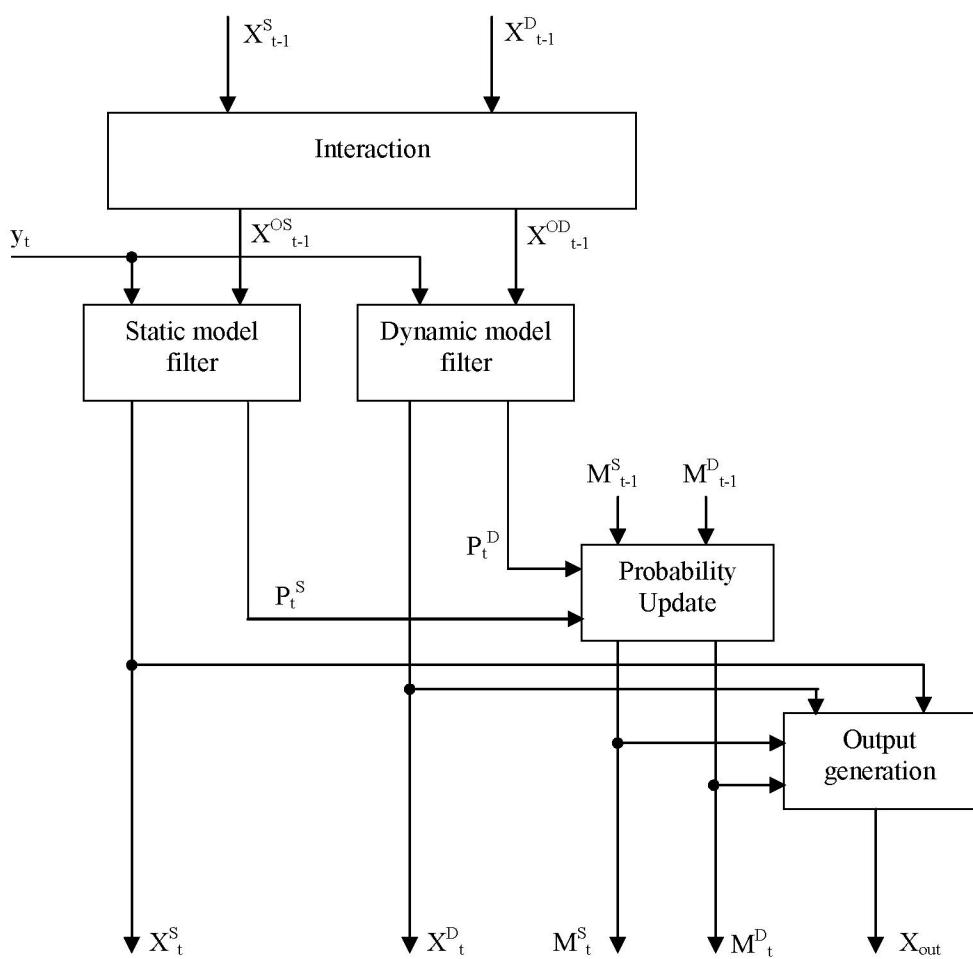


Fig. 2. Interacting Multiple Model Algorithm with Two Filters

be the corresponding filtered error variance. Then X^{oi} is the mixed state vector at the input of each filter given by

$$X^{oi} = \sum_{j=S,D} X^j \mu^{ji}; \text{ where } i = S,D \quad (18)$$

and the model probabilities μ^{ji} are given by

$$\mu^{ji} = \frac{1}{C^i} b^{ji} M^j; \text{ where } j,i=V,A$$

$$\text{and } C^i = \sum_{j=V,A} b^{ji} M^j; \text{ where } i=V,A$$

where M^j are the model weights that are calculated using normalized innovations. b^{ji} are the static model switching (transition) probabilities for the Markov chain according to which the system model switches from the static model filter to the dynamic model. Initially these values are assumed constant. C^D, C^S corresponds to the normalized constant for SMF and DMF. Subscript 'D' indicates the dynamic model and 'S' indicates the static model. The state vector $X^S(t)$ of the static model represents the channel parameters related to static receiver. The state vector $X^D(t)$ of the Dynamic model represents the channel parameters related to the dynamic receiver. The mixed error covariance during interaction is given by

$$P^{oi} = \sum_{j=S,D} \mu^{ji} \{ P^i + [X^j - X^{oi}] [X^j - X^{oi}]^T \}; \text{ where } i=S,D \quad (19)$$

where $P^i = P^i(t-1/t-1)$ is the filtered error covariance matrix defined by

$$E\{[X^i(t)-X^i(t-1/t-1)][X^i(t)-X^i(t-1/t-1)]^T\}.$$

Step 2: prediction

The prediction process for each of the filters is obtained using standard Kalman filters. The measurement $Z(t)$ is given to all filters and the normalized innovations are computed for each filter. The Kalman filtering equations for predicting the state vector are given by

$$X^i(t/t-1) = \Phi^i X^i(t-1/t-1) + Q; \text{ for } i = S,D \quad (20)$$

The filtered state vector $X^i(t-1/t-1)$ is equal to the mixed state vector X^{oi} obtained in the interaction step and hence

$$X^i(t/t-1) = \Phi^i X^{oi} \quad (21)$$

The error covariance prediction is given by

$$P^i(t/t-1) = \Phi^i P^i(t-1/t-1) (\Phi^i)^T + Q \quad (22)$$

The filtered error covariance matrix $P^i(t/t-1)$ is equal to the mixed error covariance matrix P^{oi} obtained from the interaction step and hence

$$P^i(t/t-1) = \Phi^i P^{oi} (\Phi^i)^T + Q^i \quad (23)$$

The value of the state transition matrix for the static model Φ^S is assumed as an Identity matrix. The State transition matrix for the velocity model is derived from Eq.21 using Yule Walker equations. The noise covariance matrix is expressed as $Q(t+1) = \text{diag}(\sigma_h^2(t+1))$. The power delay profile of the channel paths $\sigma_h^2(t+1) = [\sigma_{h_0}(t+1), \sigma_{h_1}(t+1), \dots, \sigma_{h_{N-1}}(t+1)]$. The observation vector is considered as a received signal vector which is common for both Kalman filters. The difference between measured and predicted quantities is defined as an innovation, it is given by

$$e^i(t) = y(t) - B^i(t) X^i(t/t-1); i = S,D \quad (24)$$

The residual error covariance matrix is defined by equation

$$S^i(t) = B^i(t) P^i(t/t-1) (B^i(t))^T + R_c \quad (25)$$

The Kalman gain is given by

$$K^i(t) = P^i(t/t-1) (B^i)^T [S^i(t)]^{-1}; i = S,D \quad (26)$$

Step 3: Model probability update

Let d^i be the residuals for model i , then model probability weight is computed as

$$M^i = \frac{1}{N_e} d^i C^i; i = S,D \quad (27)$$

where N_e is the normalization constant to ensure that

$$\sum_{i=S,D} M^i = 1 \text{ and } N_e = \sum_{j=S,D} d^j C^j$$

Step 4: filtering

The states predicted by the static and the dynamic model filters are updated using Kalman filter equations. The filter error covariance is given by

$$P^i(t/t) = [I - K^i(t) B^i(t)] P^i(t/t-1) \quad (28)$$

The filtered state vector is given by

$$X^i(t/t) = X^i(t/t-1) + K^i(t) e^i(t) \quad (29)$$

Step 5: Output generation

The resultant filter estimate is compared as a weighted sum of individual filter estimates

$$X_{out} = \sum_{i=S,D} M^i X^i \quad (30)$$

The working of the IMM algorithm is as follows; at time t , during interaction step, before the measurement $y(t)$ is received, the mixed state vector X^{oi} and the mixed error covariance P^{oi} are obtained using the previous filtered estimate $X^i(t-1/t-1)$ and the filter error covariance $P^i(t-1/t-1)$. During the time update stage, using the mixed state vector and the mixed error covariance, the best estimate of states $X^i(t/t-1)$ and $P^i(t/t-1)$ are obtained. Once the prediction is completed, the innovation and the Kalman gain $K^i(t)$ are evaluated. As soon as the measurements are available, the residuals and the model probability weights M^i are determined. During the filtering phase, the innovations are weighted by their respective gains to correct the predicted state estimates and to get a filtered state estimate and a filtered covariance. The resultant filter estimate X_{out} is computed as a weighted sum of individual filter estimates. The algorithm awaits the next measurement at time $(t+1)$ and the above process is repeated for each subsequent measurement.

V. RESULTS AND DISCUSSIONS

In this section, the performance of the proposed blind adaptive channel estimation technique is analyzed using the MB OFDM channel model. The parameters for the different channel model are given in Table.1. The additive noise used in the simulation is based on a Gaussian distribution with a variance σ^2 . We have also considered Jakes fading model with a normalized Doppler frequency of 0.0001. The parameters of the OFDM are as in the IEEE 802.15.3a standard with a bandwidth of 528 MHz that is divided into 128 subcarriers and QPSK modulation is considered. To make subcarriers orthogonal in the presence of multipath, a guard interval length of 32 subcarrier is added. The MSE analysis of the IMM based method at 10dB SNR level is shown in Fig.3. Also the MSE value for different SNR levels is shown in Fig.4 and it gives better performance than the RLS based estimation. At 20dB SNR the IMM based method gives 17dB improvement over the RLS based estimation.

The BER analysis for all four channel models using the proposed method is given in Fig.5. Also MSE comparison for static and dynamic Kalman filter model with IMM based method is given in Fig.6. However the complexity of the proposed channel estimation method is comparatively higher

plain Kalman filter, it gives better performance in fast time varying channel conditions.

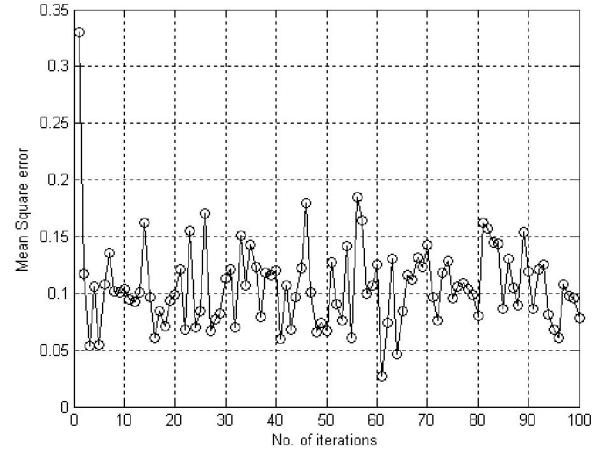


Fig. 3. MSE Analysis

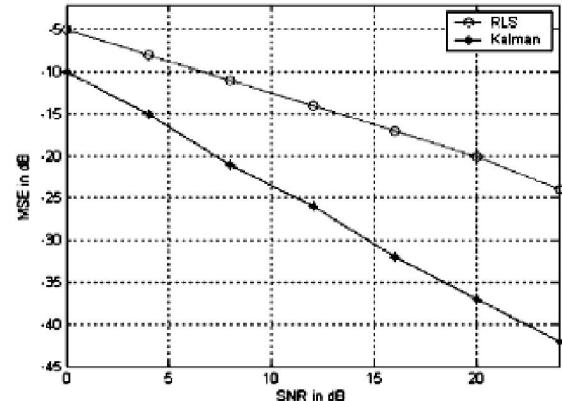


Fig. 4. MSE Comparison of RLS and Kalman Estimator

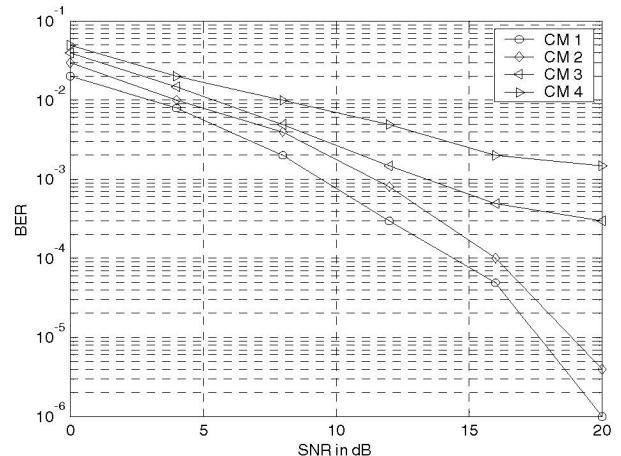


Fig. 5. BER Analysis

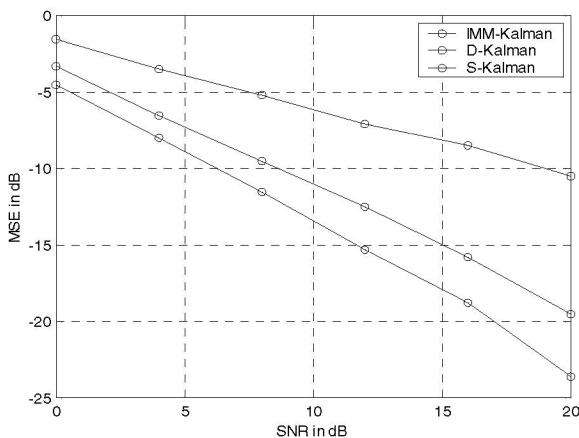


Fig. 6. MSE Comparison of IMM with S&D Kalman

VI. CONCLUSION

We have considered the problem of blind channel estimation in MB OFDM systems. The IMM based Kalman filter model is proposed to estimate channel parameters for frequency selective and time varying channel. The state transition matrix in the Kalman filter is derived based on Yule Walker equations. The proposed method gives better performance than blind RLS algorithm in terms of BER and MSE.

Table 1: Characteristics of UWB Channel Model

Channel Model Statistics	CM 1 LOS	CM 2 NLOS	CM 3 NLOS	CM 4 NLOS
Mean excess delay (nsec)	5.9854	10.4428	16.2088	29.1430
RMS delay (nsec)	5.6847	8.6050	14.7270	25.9955
NP (85% energy)	4.25	6.77	9.39	15.77
NP (10 dB peak)	4.5	6.94	8.59	12.88

REFERENCES

- [1] Sumit Roy, Jeff R. Foerster, V. Srinivasa Somayazulu, Dave G. Leeper. Ultra wideband Radio Design: The Promise of High-Speed, Short-Range Wireless Connectivity. *Proceedings of the IEEE*, 92(2):295 – 311, Feb. 2004.
- [2] Multiband OFDM Physical Layer Proposal for IEEE 802.15 Task Group 3a. www.ieee802.org/15/
- [3] Domenico porcino and Walter Hirt, “Ultra-wide band radio technology: potential and Challenges ahead”, IEEE communication magazine, July 2003.
- [4] M.Z. Win and R.A Scholtz, “Characterization of ultra-wide bandwidth wireless indoor communication channel: A communication theoretical view”, IEEE JSAC, Vol. 20, no.9, pp 1613-1627, Dec. 2002.
- [5] A.Saleh and R.Valenzuela, “A statistical model for indoor wireless multipath propagation”, IEEE JSAC, Vol no-2, pp 128-137, Feb. 1987.
- [6] A.F.Molisch, “Channel models for Ultra-wide band Personal Area Networks”, IEEE Wireless communication, December, 2003.
- [7] J. Foerster. Channel Modeling Subcommittee Report Final (doc.: IEEE802-15-02/490rl-SG3a). IEEE P802.15 Working Group for Wireless Personal Area Networks (WPANs), Feb. 2002. <http://grouper.ieee.org/groups/802/15/pub/2002/Nov02>.
- [8] L.J. Cimini, Jr., “Analysis and simulation of digital mobile channel using orthogonal frequency division multiplexing”, IEEE Trans. Comm., Vol.33.no.7, pp 665-675, July 1985
- [9] Sinemcoleri, Musthafa Ergen, Anuj Puri and Ahemad Bahai, “A study of channel estimation in OFDM system”, IEEE Vehicular Technology conference, 2003-Spring.
- [10] Jan-Jaap van de Beek, Ove edfors and Per Ola Borjesson, “On channel Estimation in OFDM systems”, in proceedings of IEEE Vehicular Technology conference (VTC’95), vol.2, pp. 815-819, Chicago, USA, July 1995.
- [11] Xenofon G. Doukopoulos and George V.Moustakides, “Blind adaptive channel estimation in OFDM systems”, IEEE ICC 2004, Vol.4, 20-24, June 2004.
- [12] P. Schramm and R. Muller, “Pilot symbol assisted BPSK on Rayleigh fading channels with diversity: Performance analysis and parameter optimization,” *IEEE Transaction on communication*, vol. 46, no. 12, pp. 1560–1563, 1998
- [13] Wei Chen and RuiFeng Zhang, “Estimation of time and frequency selective channels in OFDM systems: A Kalman filter structure”, Wei Chen and RuiFeng Zhang, IEEE GLOBECOM 2004.
- [14] T.S.Rappaport, “Wireless Communication”, Prentice Hall, 1996.
- [15] Simon Haykin, “Adaptive Filter Theory”, Prentice Hall, 3rd edition, 1996