AN ADVANCED OFDM RECEIVER WITH BAYESIAN LEARNING AND ZERO FORCING

DR.R.Shankar[1], M.Martina priya[2], V.Priyadharshini[3]

[1]*Professor, Electronics and Communication Engineering, Jeppiaar SRR Engineering College, Chennai, TN*
[2,3]*Student, Electronics and Communication Engineering, Jeppiaar SRR Engineering College, Chennai, TN*

Abstract - *Channel estimation in an Orthogonal Frequency Division Multiplexing (OFDM) based broadband system, over a selective channel is one of the challenging task. Block Sparse Bayesian learning was proposed to address the challenges, but it has resulted in considerable Inter Carrier Interference (ICI) and Inter Symbol Interference (ISI).Thus Bayesian learning using Zero Forcing technique is proposed in this work for OFDM receiver operating over fast time varying channel. This technique has excellent channel estimation performance even with a very small number of channel expansion coefficients employed in the algorithm, resulting in substantial reduction of the computational complexity along with reduced symbol error rate, moreover it overcomes ICI and ISI in this system.*

***Key Words*: OFDM, ICI, ISI, Bayesian learning, zero forcing**

1. INTRODUCTION

OFDM systems operating over fast time-varying channels experience orthogonally loss between all system subcarrier frequencies. As a result, the observed signal is affected by inter carrier interference (ICI), which can severely degrade the receiver performance. A wide range of algorithms have been proposed in the literature to suppress or mitigate ICI. It typically iterate between channel estimation, ICI cancellation and data detection. Among these we mention receivers implementing decision-feedback equalization (DFE), such as that proposed in which performs channel estimation and ICI cancellation in the frequency domain. Similar modeling is employed in to design a channel estimator using approximate message passing techniques. At each iteration the algorithm computes the hard estimate of the data symbol modulating a subcarrier, after having canceled the ICI estimated at the previous iteration .Using hard symbol estimates, and hence not accounting for uncertainties in the symbols decisions, is detrimental to the performance of the receiver when it operates over very fast time-varying channels. To overcome the above shortcomings, an algorithm that iterates between estimation of the channel time-varying weights and noise precision, ICI cancellation, detection and decoding of the signals in one transmission frame. The algorithm is developed using two main tools: block-sparse Bayesian learning (BSBL) which is a Bayesian formulation of compressed sensing and the mean-field belief-propagation (MFBP) framework appertaining to variation Bayesian inference. The BSBL methodology was recently applied to other communication problems such as estimating MIMO channel responses or channel responses which exhibit delay clustering while MF-BP was previously used for designing iterative receiver algorithms, even though considerable amount of ICI and ISI are encountered. The proposed algorithm includes zero forcing method. Zero forcing ensures that the interferences from other users are forced to zero at each receiver by eliminating all inter-user interferences. Simulation results show that our receiver algorithm outperforms selected reference algorithms and achieves BER performance higher.

2. SYSTEM MODEL

An OFDM transmission of B symbols is considered. During the ith transmission interval, i ∈ [B − 1], a vector which contains ui ∈ {0, 1} K of information bits is encoded with a code rate R and interleaved into the vector ci = [(c (0) i) T, (c (ND−1) i) T] T with entries c (k) i ∈ {0, 1} Q, k ∈ [ND − 1], RNDQ = K. The code vector ci is modulated onto a vector of ND complex symbols that are interleaved with NP pilot symbols producing the symbol vector xi ∈ C N , N = NP + ND. The mth entry xi [m] of xi is a pilot symbol if m ∈ P and a data symbol if m ∈ D 1 . The vector xi is passed through an inverse DFT block to yield the vector si to which a µ-sample long cyclic prefix (CP) is prepended. A frame of B OFDM symbols is sent over a time varying channel with response composed of L˜ multipath components: g˜(t, τ)= h˜ l(t)δ (τ − τ˜l), where h˜ l(t) and τ˜l model the time-varying gain and delay of the lth multipath component . The receiver observes a signal which is the convolution of the transmitted signal and the TV-CR g˜(t, τ) corrupted by additive white Gaussian noise. This signal is lowpass filtered sample.The remaining samples vectors that are passed through a DFT block, yielding yi = H˜ ixi + wi =diag [H˜ i]xi + ˜zi + wi . The vector ˜zi ∈ C N collects the ICI at all subcarriers.

2.1BLOCK DIAGRAM

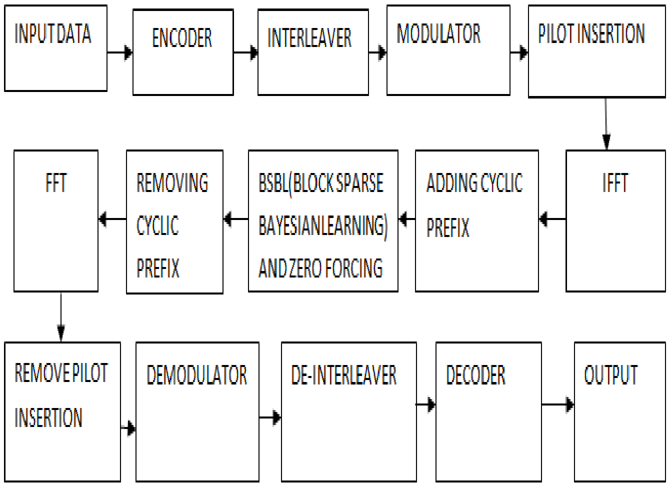

Fig: Block diagram of OFDM receiver

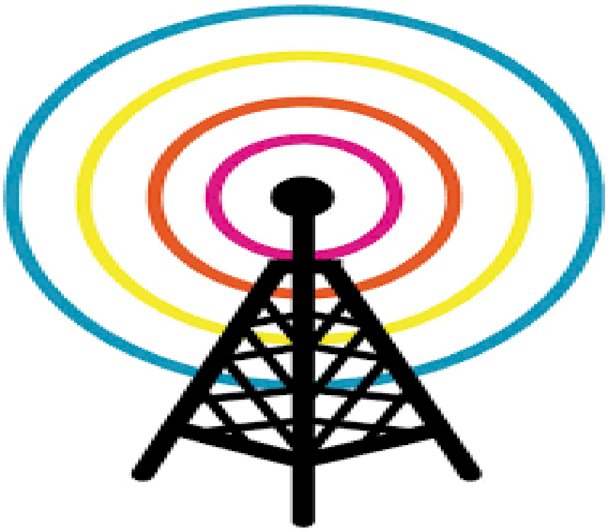

Fig: Standard Antenna

3. PROPOSED ITERATIVE RECEIVER

The orthogonal frequency-division multiplexing systems with ICI due to insufficient cyclic prefix and/or temporal variations causes ISI and ICI. Therefore, two techniques are used for equalization of ICI. The first, called block-sparse Bayesian learning (BSBL)which is a Bayesian formulation of compressed sensing and the mean-field belief-propagation (MFBP) framework appertaining to variation Bayesian inference. An algorithm that iterates, channel time-varying weights and noise, ICI cancellation, detection and decoding of the signals. Genie aided channel estimator (GAE) method access, the channel sparsity and iteratively canceling ICI and performs estimation with known matrix and noise variance also Compares with the benchmark receivers.

Zero forcing beamforming technique is used to reduce the ICI. For beam forming, preceding design are employed. Pre-coding is employed to separate the user signals, thereby mitigating multiuser interference and increasing the system capacity. In a multiuser system characterized by interferences, the implementation of an appropriate precoding method can considerably improve the system performance.. Zero-Forcing technique ensures that the interferences from other users are forced to zero at each receiver by counseling all inter-user interferences. The multiuser interferences are totally eliminated by projecting each stream onto the orthogonal complement of the inter-user interference. It takes into account the inter-user interference but neglects the effects of noise.

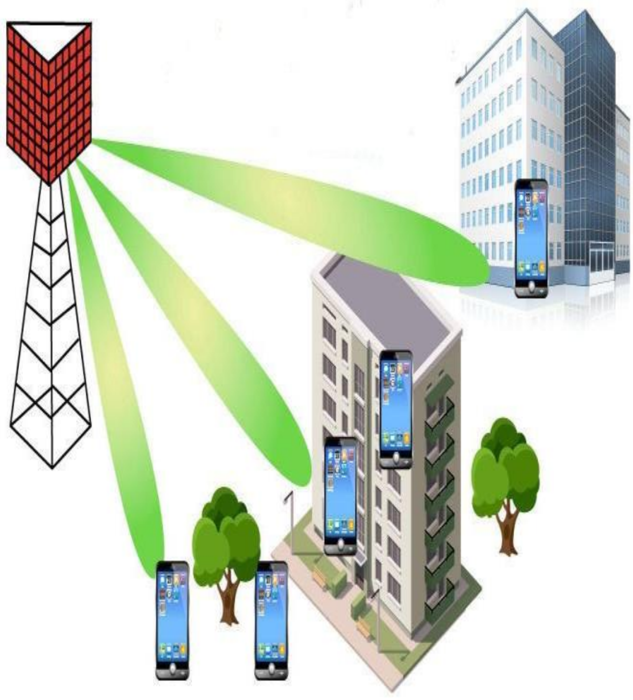

Fig : Zero forcing beam forming

4. PROPOSED RECEIVER ALGORITHM

To enforce the block sparse structure, we employ BSBL. BSBL is a Bayesian framework for compressed sensing which “explores and exploits the intra-block correlation” i.e. makes use of the correlation between the entries of a block to retrieve block-sparse variables. This is accomplished by imposing a prior distribution for the variable of interest which encourages block sparse estimates. Due to the significant Doppler shift, which results in a time-frequency doubly-selective (DS) channel. The DS channel features a large number of channel coefficients, which introduces inter-carrier Interference

(ICI) and forces the need for allocating a large number of pilot subcarriers. algorithm is based on the space alternating generalized expectation maximization (SAGE) technique which is particularly well suited to multicarrier signal formats leading to a receiver structure that also incorporates inter channel interference (ICI) cancellation. The algorithm define the set of variable nodes connected to the factor node f as N (f), and similarly, the set of factor nodes connected to a variable node θ as N (θ). Following the MF-BP framework we divide the set of factor nodes into two disjoint sets. The MF (BP) subgraph contains the nodes of the factor in the set FMF = {fp, fn, fa, foi } FBP = {fmn,k , fcn , fbn,v }.It estimates the BEM coefficients,retrieving the block sparse structure,estimating the noise precision, canceling ICI and decoding. The implicit ICI cancellation: before updating µi,dk , the ICI caused by all xi [dj], dj ∈ D, dj 6= dk is removed from the received signal yi , and a nearly interference-free signal is employed instead. Propagating BP messages through nodes fmi,k and fci corresponds to classical demapping and decoding respectively. The model of the approximate channel matrix Hi , for a given selection of the basis functions Ψ, the only unknown variables are the vectors αl used to model hl(t). With this approximate model, we circumvent the explicit estimation of the multipath delays τ˜l , l ∈ [L˜ −1] and the number of multipath components L˜ in g˜(t, τ). Instead, the DL entries of α need to be estimated. Since only a few hl(t), l ∈ [L−1] are expected to be non-zero, we postulate that Hi can approximate H˜ i well with only a few non-zero vectors αl . This implies that the vector α will have few non-zero entries occurring in blocks of length D, i.e. the vector α is block-sparse. Assuming a block-sparse α enables the use of compressed sensing tools to retrieve its entries.

BENCHMARKER	IMPLEMENTATION
RxAR(neglects ICI)	A sparse channel estimator
RxRef-ss and RxRef-spaced delays estimates hard symbols	-Modified with iterative decoding. -Knows noise variance.
GAR(genie) Cancels ICI.	-perfect channel information. -knows noise variance.
RxBEM-sparse	-cancels noise.
ZF(Zero forcing)	-cancels ISI,ICI perfectly

Fig: Benchmark receivers.

4.1. SOFTWARE SPECIFICATION

MATLAB is a high-performance language for technical computing. It integrates Computation, visualization, and programming in an easy-to-use environment where Problems and solutions are expressed in familiar mathematical notation. MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations. Also it is a flexible language compared to others, because it is easy to evaluate the performance of the system by analyzing the capacity, effective rate, outage probability, BER,etc. As it deals with matrix it can have an enough solution space with a pool of inputs. Hence we implement Matlab in Communication projects.

5. GRAPH

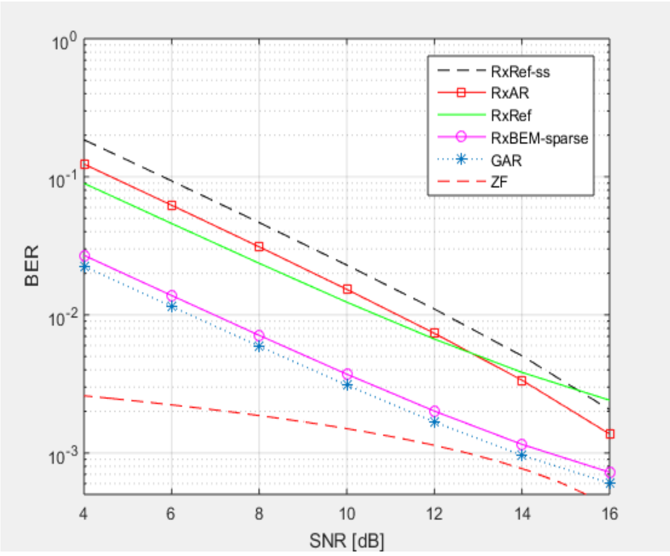

Fig:BER VS SNR

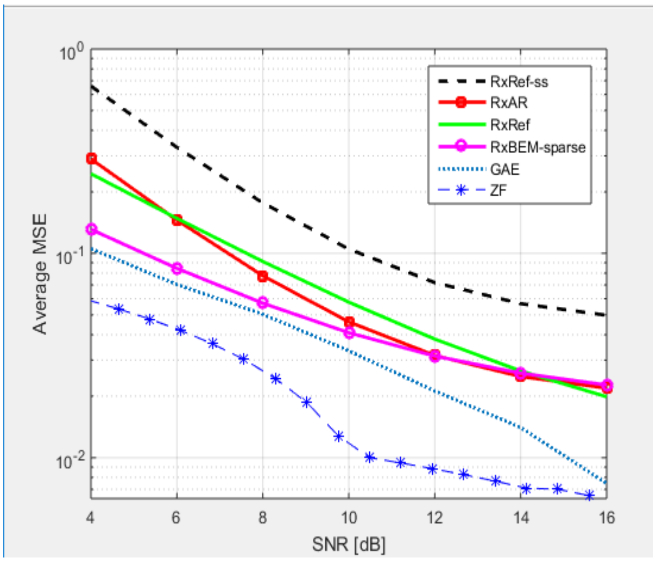

Fig:Average MSE vs SNR.

It describes about various iterative receiver such as GAR (Genie Aided receiver),RxBEM-sparse(Block sparse Bayesian learning),RxAR(Autoregressive receiver) and ZF(Zero forcing) methods which reduces Inter carrier Interference. Average Mean square error of the channel frequency response versus SNR(Signal to noise ratio) are simulated. It describes about various techniques which reduces Inter carrier interference and Inter symbol interference. Out of those, Zero forcing techniques cancels Inter symbol interference and Inter carrier interference greater than the previous techniques.

5. NUMERICAL EVALUATION

The number of multipath components L˜ is drawn from a Poisson distribution with mean μL˜ . Given L˜, to each component l ∈ [L˜ − 1] a random vector (˜τl , zl , ϕl , [ϑl,k, çl,k; k ∈ [M − 1]]) is associated: the delay τ˜l is uniformly distributed on [0, μTs]; given τ˜l , the gain zl is a zero-mean complex Gaussian variable with variance v0exp(−m0τl); the mean azimuth ϕl and the phases çl,k are drawn from a uniform distribution on [0, 2π). Given ϕl , the azimuths ϑl,k are drawn from a von Mises distribution with mean and concentration κv. We abbreviate the receiver implementing the proposed algorithm as RxBEM-sparse. For channel estimation benchmarking we use a genie-aided channel estimator (GAE) which performs LMMSE estimation of α with known dictionary matrix and noise variance. we observe that the average MSE for all receivers exhibits a saturation when they operate in the high SNR regime. This behavior is due to the estimation model mismatch stemming from the choice of basis, the fixed delay grid and the errors in the estimates of the data symbols. In particular, RxRef– ss exhibits the highest sensitivity to these mismatches as it employs a delay vector with Ts-spaced entries. Even though there is still a notable gap between the average MSEs of RxBEM-sparse and GAE, RxBEMsparse performs very closely to GAR in terms of BER outperforming all benchmark receivers. This shows that efficient receivers can accommodate some errors in the estimation of the channel and still operate closely to the optimal performance. Canceling ICI using hard symbol estimates proves detrimental to the BER performance of both RxRef and RxRef–ss, particularly in the high SNR regime. In this case, an algorithm which neglects ICI, such as RxAR may be preferred. Zero forcing method neglects the noise ,ICI and ISI perfectly.

6. CONCLUSION

Developed a tractable algorithm for OFDM receivers operating over fast time varying channel which employed BSBL with zero forcing technique. It over comes the task of explicitly estimating the delays. As the transmission of symbols through a sparse channel at a high data rate which results in inter symbol interference (ISI). To reduce this effect and ensure accurate decoding of the transmitted symbols, zero forcing is implemented. This increases the system capacity, reduces complexity of the system. Overcomes the task of estimating delays. The receiver implementing this algorithm successfully cancels ICI and performs greater than block-sparse Bayesian learning.

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