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Dynamic Channel Estimation for MIMO-Constant Envelope Modulation

Ehab Mahmoud Mohamed[1,2] , Osamu Muta[3], and Hiroshi Furukawa[1]
[1] Graduate School of Information Science and Electrical Engineering, Kyushu University, Motooka 744, Nishi-ku, Fukuoka 819-0395, Japan.
[2] Permanent: Electrical Engineering Department, Faculty of Engineering, South Valley University, Egypt.
[3] Center for Japan-Egypt Cooperation in Science and Technology, Kyushu University, Motooka 744, Nishi-ku, Fukuoka 819-0395, Japan.
ehab@mobcom.ait.kyushu-u.ac.jp, {muta,furukawa}@ait.kyushu-u.ac.jp.

ABSTRACT

The Multi-Input Multi-Output (MIMO)-Constant Envelope Modulation MIMO-CEM is introduced as power and complexity efficient alternative to MIMO-OFDM for wireless backhaul networks. Due to a low resolution ADC (1-bit in the default operation) employed in the MIMO-CEM receiver, MIMO-CEM channel estimation is considered as one of the major challenges toward its real application. A block based adaptive channel estimator was proposed by the authors to estimate MIMO-CEM channel in static and quasi-static channel conditions. In this scheme, channel parameters are iteratively estimated by replicating the received preamble signals. In addition, to accurately estimate MIMO-CEM channel in presence of severe quantization errors caused by a low resolution ADC on the receiver side, the authors proved that Code Division Multiplexing (CDM) preambles transmission is effective in estimating MIMO channel state information. Although wireless backhaul channel is generally assumed to be static and quasi-static, it suffers from channel fluctuations in actual situation. Therefore, the objective of this paper is to present a decision directed channel estimation (DDCE) to track MIMO-CEM channel fluctuation in high Doppler frequency conditions, and clarify the effectiveness of MIMO-CEM adaptive estimator in time varying channel conditions. The performance of proposed DDCE is compared with that of Pilot Assisted (PAS) linear interpolation dynamic channel estimation. For performance evaluations, different Doppler frequencies are assumed to prove the effectiveness of the scheme even in high channel variations. Simulation results prove that MIMO-CEM is applicable to dynamic channel conditions with various Doppler frequencies.

KEYWORDS

MIMO, Constant envelope modulation, Decision directed channel tracking, Adaptive channel estimation, Low resolution ADC.

1 INTRODUCTION

Multi-Input Multi-Output Constant Envelope Modulation, MIMO-CEM, has been introduced as an alternative candidate to the currently used MIMO-Orthogonal Frequency Division Multiplexing (OFDM) especially for wireless backhaul network applications [1]-[3]. One of the major disadvantages of the OFDM is that the transmit signal exhibits noise like statistics with high Peak to Average Power Ratio (PAPR). This OFDM signal requires high power consumption analog devices especially for RF power amplifier (PA) [4]-[8] and analog-to-digital converter (ADC) [9]

[10]. Due to the stringent linearity requirements on handling OFDM signal, nonlinear power efficient PA like class C cannot be used for OFDM transmission. Instead, linear power inefficient PA should be used like class A and class A/B, which gets OFDM a power consuming modulation scheme. In consequence, many efforts have been made so far to solve this vital problem in OFDM systems for the recent years [4]-[8]. All these drawbacks prevent OFDM from scalable design when it is extended to MIMO due to Hardware complexity [11] [12].

To cope with this issue, the authors suggested using Constant Envelope Modulation (CEM) as a method to improve power-efficiency at PA on the transmitter side and reduce power consumption at ADC on the receiver side [1] [3]. In this system, constant envelope Phase Modulation (PM) is used at the transmitter. Since PM signal can be viewed as differential coded frequency modulated (FM) signal, information is carried over frequency domain rather than over amplitude domain. Therefore, it is allowed to use nonlinear PA at transmitter subject to reducing spurious emission. Till now, most of the studies on PA have been investigated for linear modulation, i.e., PA has to be designed to achieve good trade-off between the requirement of linearity and the improvement of power efficiency. On the other hand, CEM systems alleviate the requirement of linearity at PA and therefore drastic improvement of power efficiency is highly expected as compared with linear modulations [13].

On the receiver side, radio frequency (RF) or intermediate frequency (IF) sampling results in allowing us to use low resolution ADC subject to shorter sampling interval than that required for baseband sampling. The authors suggested using 1-bit ADC operated at IF sampling as CEM default operation. [1] [3]. Although compensation of high-nonlinearity caused by 1-bit ADC requires advanced digital signal processing techniques on the receiver side, there will be a great reduction in power consumption and hardware complexity. For example, by only using 1-bit ADC, there is no need for the complex analog Automatic Gain Control (AGC) circuit which greatly reduces CEM power consumption and complexity, especially when it is extended to MIMO, where each MIMO branch needs its own AGC circuit [14]-[16]. In addition, this low resolution ADC with IF sampling removes most IF analog stages (analog mixer, analog LPF and anti aliasing filter), which reduces receiver complexity. In contrast, it is a high power consuming to design ADC for OFDM systems at the IF band because of its high resolution, which gives us another superiority of CEM over OFDM regarding power consumption and complexity [17].

On the other hand, OFDM has higher spectral efficiency than CEM. This drawback of CEM is diminished by introducing MIMO; CEM should be subjected to higher MIMO branches than OFDM. Although, such a MIMO basis design of the proposed CEM transceiver necessitates high computational power required for digital signal processing, we can view the concern with optimistic foresight because cost for digital signal process is being reduced every year thanks to rapid progress on digital circuit evolution. A little improvement in power efficiency of major analog devices such as PA has been observed for the last few decades. In contrast, we have seen

drastic improvements of digital devices in their power consumption and size for the same decades [18] [19].
In MIMO-CEM receiver, the authors have proposed to use Maximum Likelihood Sequence Estimation (MLSE) as a nonlinear equalization to deal with the inter-symbol interference (ISI) caused by the multi-path channel and the severe quantization error caused by the low resolution ADC [3]. Such a nonlinear equalizer needs accurate multipath channel states information to replicate the received signal correctly, which is hard task in presence of the low resolution ADC. This is because the received signal amplitude fluctuation is completely removed in the default 1-bit resolution operation and seriously affected even in a few bit resolutions. Therefore, MIMO-CEM channel estimation in presence of the low resolution ADC is a big challenge to the real application. In [3], the authors have proposed channel estimation method for SISO (MIMO)-CEM systems in static and quasi-static channels, where channel parameters are iteratively estimated by an adaptive filter which minimizes the error between the actual received preamble and a generated replica of it. Correlator estimator is used as initial channel estimation to speed up adaptive channel parameters' convergence rate. To extend SISO-CEM channel estimation to MIMO-CEM, the authors investigated Code Division Multiplexing (CDM) and Time Division Multiplexing (TDM) MIMO preambles transmission [20]. They clarified that it is required to use CDM preambles for accurate MIMO channel estimation in presence of large quantization noise caused by 1-bit ADC.
The objective of this paper is to present a decision directed channel estimation (DDCE) technique to estimate and track MIMO-CEM channel fluctuation in dynamic channel conditions, where the adaptive channel estimator in [3] is extended to dynamic one. In MIMO-CEM systems with DDCE, channel estimates during current data block are estimated by using the decided values of the previous data block. Dynamic channel estimation is more challengeable than quasi-static one because dynamic channel estimation and tracking has to be achieved during highly quantized received data, where all signal amplitude information is severely affected by a low resolution ADC and completely removed in the 1-bit case. For the purpose of comparison, we evaluate a linear interpolated pilot assisted (PAS) channel tracking for SISO-CEM (SISO-CEM PAS), where two preambles are allocated at the beginning and the end of the frame. Channel estimates at these two positions are used to estimate channel variation between these preambles using linear interpolation.
The rest of the paper is organized as follows. Section 2 gives detailed construction of the MIMO-CEM transceiver system. The MIMO-CEM adaptive channel estimator for static and quasi-static channels is given in Sec. 3. Section 4 gives the proposed SISO (MIMO)-CEM block based DDCE and the linear interpolated pilot assisted channel tracking (PAS). Performance evaluations are given in Sec. 5 followed by the conclusion in Sec. 6.

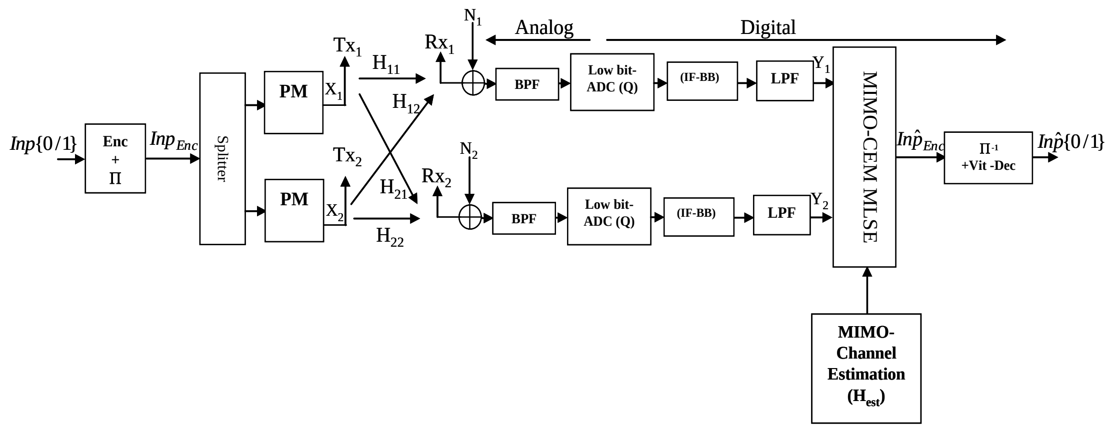

Figure 1. The 2x2 MIMO-CEM transceiver.

2 MIMO-CEM TRANSCEIVER SYSTEM

Figure 1 shows the system block diagram of 2x2 MIMO-CEM. In Fig.1, the input binary information data (*Inp{0/1}*) is convolutional-encoded and interleaved (Enc + Π) (Inp_{Enc}) in order to enhance BER performance of MIMO-CEM especially in the default 1-bit ADC operation. Inp_{Enc} is then split into number of streams equal to the number of the transmit antennas *Mt*. Constant envelope PM modulation is applied to each data stream using differential encoder followed by MSK or GMSK frequency modulation which results in constant envelope transmitted MIMO signals X_q, $1 \le q \le Mt$. The received signals are affected by MIMO Rayleigh fading multipath channels from transmit antenna *q* to receive antenna *p*, e.g., H_{pq}, $1 \le p \le Mr$, $1 \le q \le Mt$ where *Mr* is the number of receive antennas, and Additive White Gaussian Noise (AWGN) N_p associated with each receive antenna *p*. At each receive antenna and in the IF band, analog BPF filter is used to improve Signal to Noise power Ratio (SNR) of the IF signal corrupted by AWGN noise. After that, the signal is converted into digital on using low resolution ADC (Q) sampled at IF band and digitally converted into baseband (IF-BB) and low pass filtered (LPF) (Y_p).

The 1-bit ADC at each receive antenna induces high nonlinear distortion expressed as a hard limiter function:

$$Hrdlmt(\Theta) = \begin{cases} 1 \ \ if \ \ \Theta \ge 0 \\ -1 \ \ if \ \ \Theta < 0 \end{cases} \qquad (1)$$

Hence, the received LPF vector at each receive antenna Y_P can be expressed as:

$$Y_p = f(\sum_{q=1}^{Mt} \mathbf{H}_{pq} X_q + N_p), \ 1 \le p \le Mr \quad (2)$$

where *f* denotes the nonlinear *Hrdlmt* function Eq.1 followed by the linear LPF function $f(\Theta) = LPF(Hrdlmt(\Theta))$. $\mathbf{H}_{pq}$ denotes channel Toeplitz matrix of size *B*x*B* from transmit antenna *q* to receive antenna *p*, where *B* is the transmitted X_q and received Y_p streams length, given by:

$$\mathbf{H}_{pq} = \begin{bmatrix} h_{pq0} & 0 & 0 & 0 & 0 & \ldots\ldots & 0 \\ h_{pq1} & h_{pq0} & 0 & 0 & 0 & \ldots\ldots & 0 \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ h_{pq(M-1)} & h_{pq(M-2)} & \ldots\ldots & h_{pq0} & 0 & \ldots\ldots & 0 \\ 0 & h_{pq(M-1)} & h_{pq(M-2)} & \ldots\ldots & h_{pq0}. & \ldots\ldots & 0 \\ . & . & . & . & . & . & . \\ 0 & 0 & \ldots\ldots & 0 & 0 & 0 & h_{pq(M-1)} \end{bmatrix} \quad (3)$$

where $H_{pq} = [h_{pq0} \ \ h_{pq1} \ldots\ldots h_{pq(M-1)}]^T$ denotes the multipath channel vector of length M and suffix T means transpose. $X_q = [x_q(0)\ x_q(1) \ldots x_q(B-1)]^T$, $Y_p = [y_p(0)\ y_p(1) \ldots y_p(B-1)]^T$ and N_p is the associated AWGN.

In MIMO-CEM, maximum likelihood sequence estimation (MLSE) is used as nonlinear equalization to compensate for error caused by nonlinear quantization given by Eq. (2). The MLSE equalizer estimates both ISI and quantization error when it equalizes the channel distortion. The MLSE equalizer searches all possible transmitted MIMO candidates under the effect of the nonlinear function f using highly estimated MIMO channels, and the most likely transmitted vector sequence is chosen.

Let $Y_{tot} = [Y_1^T\ Y_2^T \ldots Y_{Mr}^T]^T$ denotes the vector that contains all received antenna vectors, and let the vector that contains all transmitted PM streams be $X_{tot} = [X_1^T\ X_2^T \ldots X_{Mt}^T]^T$. Let the channel matrix that contains all estimated Toeplitz matrices be:

$$\mathbf{H}_{est}^{tot} = \begin{bmatrix} \mathbf{H}_{est11} & \mathbf{H}_{est12} & \cdots\cdots & \mathbf{H}_{est1Mt} \\ \mathbf{H}_{est21} & \mathbf{H}_{est22} & \cdots\cdots & \mathbf{H}_{est2Mt} \\ . & . & . & . \\ . & . & . & . \\ \mathbf{H}_{estMr1} & \mathbf{H}_{estMr2} & \cdots\cdots & \mathbf{H}_{estMrMt} \end{bmatrix} \quad (4)$$

Then, MIMO-CEM MLSE equalizer can be expressed as:

$$In\hat{p}_{Enc} = \arg \min_{X_{tot}^d \in \{X_{tot}^1, \ldots, X_{tot}^D\}} \left\| Y_{tot} - f(\mathbf{H}_{est}^{tot} X_{tot}^d) \right\|^2 \quad (5)$$

where $D = 2^J$ denotes the number of candidate sequences X_{tot}^d in MLSE with memory equal J, and J is a function of the channel memory M and number of transmit antennas Mt. Therefore, the MLSE has the ability to equalize the received MIMO signal, with an acceptable BER, even if it is affected by the high nonlinear hard limiter (1-bit ADC) under the constraints of highly estimated MIMO channels (which is our main concern in this paper). Finally, De-interleaver and Viterbi decoding (Π^{-1}+Vit-Dec) are carried out for error correction, and output the estimated transmitted data $In\hat{p}\{0,1\}$.

3 CHANNEL ESTIMATION FOR MIMO-CEM SYSTEMS

In this section, we give an overview of the adaptive channel estimator proposed by the authors to estimate SISO (MIMO)-CEM channel in static and quasi-static channels [3]. First, we give an overview of the SISO-CEM channel estimation, and then we show how the authors extended it to MIMO-CEM channel estimation.

3.1 SISO-CEM Adaptive Channel Estimation

The main idea of the channel estimation proposed in [3] is to replicate the received preamble signal in presence of the nonlinear function *f*. The estimated channel vector is determined so as to minimize the error between the actual received preamble and the replicated one, where an adaptive algorithm is used to minimize this error iteratively. Figure 2 shows the block diagram of SISO-CEM adaptive filter based channel estimator, where constant envelope PM modulated PN sequence X is transmitted as a known preamble training sequence for the adaptive channel estimator. An example of the preamble complex MSK baseband signal X_b is depicted in Fig.3. The differential encoder before the MSK modulation gets the PN information to be on the peaks of X_b. The preamble sequence in this example consists of 7-chip PN sequence {1,j,1,-j,1,-j,-1} whose auto-correlation function exhibits

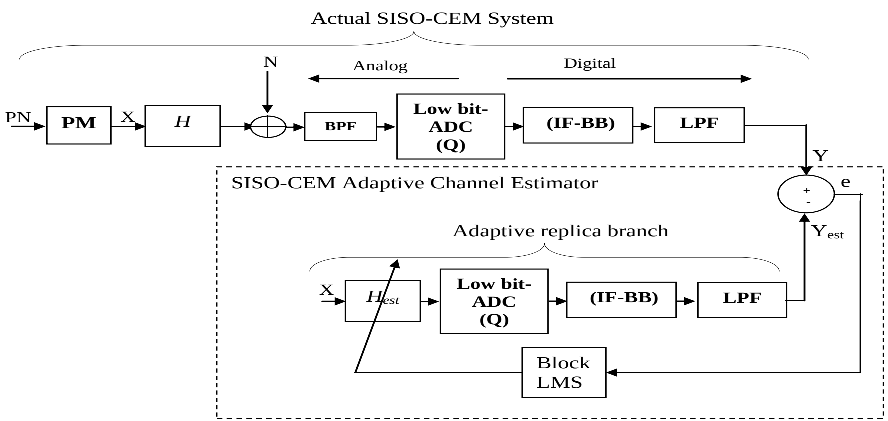

Figure 2. The proposed SISO-CEM adaptive channel estimator.

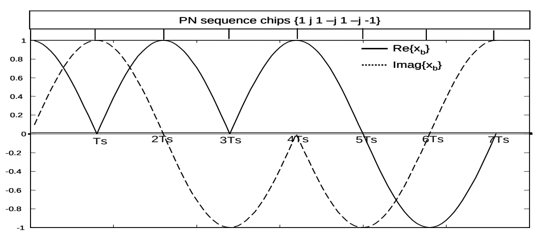

Figure 3. The constant envelope complex baseband signal X_b.

sharp peak amplitude. T_s is the chip (symbol) duration.

The received preamble signal after frequency-down conversion and LPF in digital domain is denoted as Y, for 1-bit ADC:

$$Y=f(\mathbf{H}X+N) \tag{6}$$

where **H** is the SISO channel Toeplitz matrix Eq. (3). The replicated received signal Y_{est} is obtained by applying the known preamble X to the adaptively estimated channel vector H_{est} and a given ADC function, for 1-bit ADC:

$$Y_{est} = f(\mathbf{H}_{est}X) \tag{7}$$

Then, the adaptive estimator calculates the error between the actual received preamble vector Y and its replica Y_{est}. The channel parameters H_{est} is determined so as to minimize the Mean Square Error (MSE) between Y and Y_{est} given by:

$$\text{MSE} = \overline{\left\| Y - Y_{est} \right\|^2} \tag{8}$$

where $\|\Psi\|$ and $\overline{\Psi}$ denote the absolute and average values of vector Ψ respectively. Therefore, for no AWGN, the estimator tries to adaptively find H_{est} whose characteristics satisfy this nonlinear equation:

$$f(\mathbf{H}_{est}X) = f(\mathbf{H}X) \tag{9}$$

From Eq. (1), the definition of the nonlinear function f and Eq. (9), there are infinite numbers of H_{est} that can solve the nonlinear equality of Eq. (9), i.e., there are many local minimums of the MSE given by Eq. (8) as a function of H_{est}. Hence, the adaptive estimator will converge to one of these local minimums results in H_{est} that may not equal actual H but satisfies Eq. (9), i.e. finding H_{est} that mimics the effect of H upon the transmitted signal when 1-bit ADC is used at the receiver.

The finally estimated H_{est} is utilized by the CEM nonlinear MLSE equalizer, which works in harmony with the adaptive estimator by taking the same effect of the nonlinear function f into account, for further symbols equalization. The Block LMS algorithm used in the adaptive process is [21]:

$H_{est}\,(n+1) =$

$$H_{est}\,(n) + \frac{u(n)}{B} \sum_{i=0}^{B-1} X_b^{\bullet}(nB+i)\,e(nB+i) \tag{10}$$

$$e(nB+i) = Y(nB+i) - Y_{est}(nB+i) \tag{11}$$

Where $H_{est}(n)=[h_{est0}(n)\ h_{est1}(n).....h_{est(M-1)}(n)]^T$ is the estimated channel vector of length M at iteration step n, $u(n)$ is variable step size of recursive calculation in adaptive filter, and B is the length of the complex baseband training transmitted PM signal X_b. The variable step size $u(n)$ is used to accelerate the convergence speed of the scheme so low complex estimator is obtained. Suffixes T and $\bullet$ denote transpose and complex conjugate respectively and $X_b^{\bullet}(nB+i)=[x_b^{\bullet}(nB+i)\ x_b^{\bullet}(nB+i-1)......x_b^{\bullet}(nB+i-M+1)]^T$. The channel estimator calculates the error for the entire received training preamble block stored at the receiver. After that, channel parameters H_{est} are updated once by the recursive calculation in Eqs. (10) and (11). This calculation is continued until MSE Eq. (8) becomes low enough to obtain sufficient BER performance or the number of iterations N_{train} comes to a given number. Although channel amplitude information is completely lost due to the effect of 1-bit ADC, channel information is still remained as phase rotation characteristics of the PN sequence. This information is extracted and utilized by the cross-correlation updating term in Eq. (10). Hence, the finally estimated channel is an equivalent version of the actual channel with equal total phase information.

To shorten the required number of iterations, reduce computational complexity and accelerate the convergence rate of the adaptive estimator, the authors also proposed a correlator estimator, utilizing the channel phase information in the received PN preamble sequence, to roughly estimate the initial states of $H_{est}(0)$ given by:

$$h_{est}^{(0)}(m)=\frac{1}{L}\sum_{l=0}^{L-1}Y_{(l+m)T_s}X_{b\,lT_s}^{\bullet}\ ,$$

$$m=0,\ldots,M-1 \qquad (12)$$

where L is the PN sequence length and M denotes the number of branches in the correlator bank ($L>M$). $Y_{(l+m)T_s}$ is the signal Y sampled at time $(l+m)T_s$, $X_{b\,lT_s}^{\bullet}$ is the complex conjugate of X_b sampled at every lT_s.

3.2 Extension to MIMO-CEM Channel Estimation

In order to extend SISO-CEM adaptive channel estimator into MIMO-CEM channel estimation, the authors investigated two well known techniques to estimate MIMO channels, i.e., Time Division Multiplexing (TDM) and Code Division Multiplexing (CDM) preambles transmission [20]. In MIMO TDM scheme, PN preambles are transmitted from the transmit antennas in a sequential fashion in time domain. That is, to estimate the channels associated with certain transmit antenna, this antenna is the only one allowed to transmit the preamble packet while other transmit antennas are not allowed to transmit. This can be expressed for 1-bit ADC MIMO-CEM as:

$$Y_{P\_TDM}=\underset{1\le q\le Mt}{\forall} f(\mathbf{H}_{pq}X_{q\_TDM}+N_p),\quad 1\le p\le Mr \qquad (13)$$

In contrast, in MIMO CDM technique, orthogonal preambles are simultaneously transmitted from the transmit antennas. For 1-bit ADC MIMO-CEM, this can be expressed as:

$$Y_{p\_CDM}=f\Big(\sum_{q=1}^{Mt}\mathbf{H}_{pq}X_{q\_CDM}+N_p\Big),\quad 1\le p\le Mr,$$
$$X_{q\_CDM}\in orthogonal\ \ codes \qquad (14)$$

These orthogonal codes can be generated using phase shifted PN sequences, and this phase shift is greater than the maximum expected channel length, so some sort of orthognality is maintained between the simultaneously transmitted preambles.

TDM converts MIMO channels estimation into parallel SISO channels estimation. In consequence, channels estimates H_{estpq} are estimated to satisfy the following equation (assuming no AWGN):

$$f(\mathbf{H}_{estpq} X_{q\_TDM}) = f(\mathbf{H}_{pq} X_{q\_TDM}) \quad (15)$$

where H_{estpq} is optimized to reduce the MSE between the SISO received preamble and its replicated version (as previously explained). Therefore, sufficient MIMO-CEM equalization Eq. (5) is not achieved using those SISO estimated channels. Instead, due to the nonlinear effect of the function f upon the data multiplexed MIMO signal at each receive antenna Fig.1, sufficient MIMO-CEM equalization is obtained by jointly estimate and optimize MIMO-CEM channels to satisfy this equation (assuming no AWGN):

$$Y_{estP} = Y_P$$

$$i.e., \; f(\sum_{q=1}^{Mt} \mathbf{H}_{estpq} X_q) = f(\sum_{q=1}^{Mt} \mathbf{H}_{pq} X_q), \; 1 \le p \le Mr \quad (16)$$

In CDM, the received signal amplitude is fluctuated by code multiplexing of the preambles simultaneously transmitted from each antenna. This amplitude fluctuation is removed by the 1-bit ADC at the receiver, i.e., this fact suggests that the receiver experiences the nonlinear distortion caused by the ADC upon the multiplexed MIMO signal therefore channel parameters can be optimized for MIMO-CEM. As a result, it is expected that CDM preambles transmission achieves better MIMO-CEM channel estimation performance than TDM. In order to handle CDM based MIMO-CEM channel estimation, the authors proposed MIMO-CEM Adaptive filters Bank channel estimator as an extension to the SISO-CEM adaptive estimator.

Figure 4 shows CDM based 2x2 MIMO-CEM adaptive filters bank channel estimator for simultaneously estimating H_{est11}, H_{est12} and H_{est21}, H_{est22} in order to satisfy Eq. (16) for Y_1 and Y_2 respectively. In this scheme, utilizing the property that MIMO channels are uncorrelated, H_{estpq} can be simultaneously and separately updated using the BLMS algorithm as follows:

$$H_{estpq}(n+1) = H_{estpq}(n) + \frac{u(n)}{B} \sum_{i=0}^{B-1} X^{\bullet}_{bq\_CDM}(nB+i) e_{p\_CDM}(nB+i) \quad (17)$$

$$e_{p\_CDM}(nB+i) = Y_{p\_CDM}(nB+i) - Y_{estp\_CDM}(nB+i) \quad (18)$$

The nonlinear effect of the 1-bit ADC upon the multiplexed received MIMO signal can be taken into account through using this structure results in reducing the MSE between the actual received preamble Y_{p_CDM} and its replica Y_{estp_CDM} with good optimization of Eq. (16). Utilizing the orthognality between the transmitted PN preambles X_{q_CDM}, the initial values for H_{estpq} can be estimated simultaneously using MtxMr correlator estimators; one for each H_{estpq} as follows:

$$h^{(0)}_{estpq}(m) = \frac{1}{L} \sum_{l=0}^{L-1} Y_{p\_CDM(l+m)T_s} X^{\bullet}_{bq\_CDMlT_s} \qquad m=0,..,M-1 \quad (19)$$

where $Y_{p\_CDM(l+m)T_s}$ is the LPF received signal at receive antenna p sampled at time $(l+m)T_s$, and $X^{\bullet}_{bq\_CDMlT_s}$ is the complex conjugate of transmitted baseband PN preamble from transmit antenna q sampled at every lT_s.

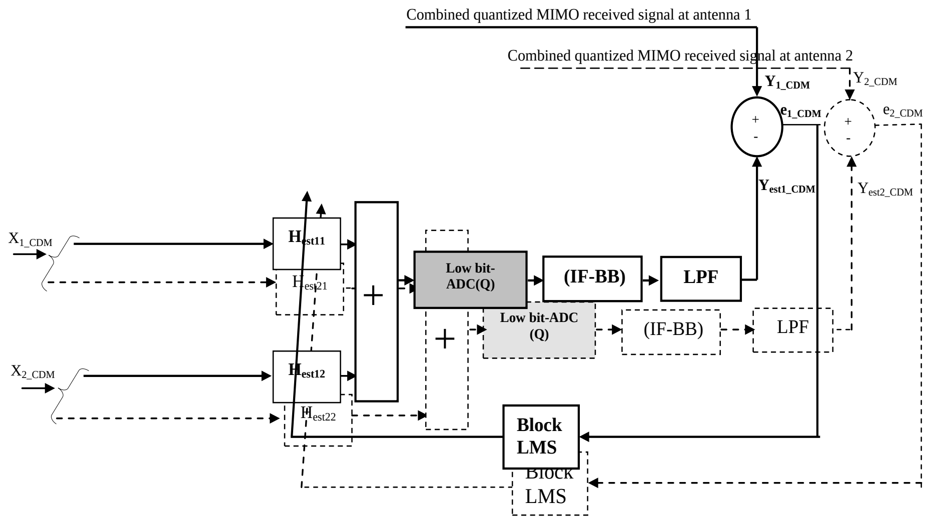

Figure 4. System configuration of the proposed channel estimator with CDM preambles transmission in 2×2 MIMO-CEM.

4 DYNAMIC CHANNEL TRACKING FOR SISO-(MIMO) CEM SYSTEMS

In this section, we propose a block based DDCE for SISO (MIMO)-CEM systems to estimate and track SISO (MIMO) -CEM channel(s) in dynamic channel conditions, and compare it with the conventional linear interpolation based dynamic channel estimation technique.

4.1 Block Based Decision Directed Dynamic Channel Estimation in SISO (MIMO)-CEM Systems

DDCE is an effective technique to track channel fluctuation during data transmission in high Doppler frequency systems [22] [23]. In this section, we present a block based DDCE for dynamic channel tracking in SISO (MIMO)-CEM systems. Figures 5 and 6 show the proposed SISO and 2x2 MIMO-CEM (Hard/Soft) DDCE construction respectively. They include the SISO and 2x2 MIMO-CEM adaptive channel estimators shown in Figs. 2 and 4 respectively.

Here, we explain the proposed scheme in MIMO-CEM case, and SISO-CEM is the same like MIMO-CEM except the number of transmit and receive antennas equal one. In the proposed scheme, the MIMO received LPF data vectors Y_1^T, Y_2^T ,...,Y_{Mr}^T are divided into blocks $Y_{1(K)}^T$, $Y_{2(K)}^T$,..,$Y_{Mr(K)}^T$, $1 \le K \le NoOfBlocks$, which results from receiving the transmitted data blocks $Inp_{(K)}$ .The proposed 2x2 MIMO-CEM (Hard/Soft) DDCE (can be generalized to any *Mt*x*Mr* MIMO-CEM) is described as follows:

1. First, MIMO channels vectors are initially estimated ($H_{est11(0)}$, $H_{est12(0)}$, $H_{est21(0)}$ and $H_{est22(0)}$) using the received LPF CDM based PN preambles Y_{1_CDM} and Y_{2_CDM} and transmitted PN preambles X_{1_CDM} and X_{2_CDM} . This initial estimation is done

using correlator and adaptive channel estimators described in Sec. 3.

2. These initially estimated channels are used to equalize the received data block $Y_{tot(1)} = [Y_{1(1)}^T \, Y_{2(1)}^T]^T$ using the MLSE equalizer Eq. (5) to obtain $In\hat{p}_{Enc(1)}$ which is de-interleaved (Π^{-1}) and Viterbi decoded (Vit-Dec) to find the estimated input data block $In\hat{p}_{(1)}$.
3. Two types of block based DDCE methods are considered in this paper, i.e., Hard and Soft DDCEs. In Hard DDCE, the output signal of the MLSE equalizer is hard decided as $In\hat{p}_{Enc(1)}$. Then, $In\hat{p}_{Enc(1)}$ is split into two streams that PM modulated to estimate $\hat{X}_{1(1)}^{Hard}$ and $\hat{X}_{2(1)}^{Hard}$ (the dashed line in Figs. 5 and 6) which are fed back to the adaptive channel estimator. Current channels vectors estimate, $\boldsymbol{H}_{est(K-1)}$ in Fig. 6, ($H_{est11(1)}$, $H_{est12(1)}$, $H_{est21(1)}$ and $H_{est22(1)}$) are estimated using ($H_{est11(0)}$, $H_{est12(0)}$, $H_{est21(0)}$ and $H_{est22(0)}$) (as the adaptive filters bank initial values, sec 3), ($\hat{X}_{1(1)}^{Hard}$, $\hat{X}_{2(1)}^{Hard}$) and ($Y_{1(1)}$, $Y_{2(1)}$).
4. In Soft DDCE, the output of error correction decoder is utilized, i.e., soft output information of the MLSE equalizer, Log Likelihood Ratio (*LLR)* of the equalizer output, is de-interleaved (Π^{-1}) and applied to soft input Viterbi decoder (Vit Dec) to obtain $In\hat{p}_{(1)}$. $In\hat{p}_{(1)}$ is encoded (Enc), interleaved decoded (Π), and split into two streams that PM modulated to obtain $\hat{X}_{1(1)}^{Soft}$ and $\hat{X}_{2(1)}^{Soft}$ (the solid line in Figs. 5 and 6). Then, $\hat{X}_{1(1)}^{Soft}$ and $\hat{X}_{2(1)}^{Soft}$ are fed back to the adaptive channel estimator. Similar to Hard DDCE, current channels vectors estimate ($H_{est11(1)}$, $H_{est12(1)}$, $H_{est21(1)}$ and $H_{est22(1)}$) are estimated using ($H_{est11(0)}$, $H_{est12(0)}$, $H_{est21(0)}$ and $H_{est22(0)}$) (as the adaptive filters bank initial values, sec 3), ($\hat{X}_{1(1)}^{Soft}$, $\hat{X}_{2(1)}^{Soft}$) and ($Y_{1(1)}$, $Y_{2(1)}$).
5. Repeat steps 2, 3 until $Y_{(K)} = Y_{(NoOfBlock)}$.

4.2 Pilot Assisted Linear Interpolation Channel Estimation

As a conventional pilot assisted (PAS) time-varying channel estimation method, we also consider a linear interpolation based technique, where channel characteristic is estimated by taking linear interpolation between two channel estimates provided by preambles at the beginning and end of the transmission frame. Linear interpolation is used to linearly estimate the channel between these two known values. For more estimation accuracy, many pilots are shuffled with the data and then higher order interpolation can be used. Although shuffling many pilots enhances the estimation accuracy, it increases the complexity and reduces the spectral efficiency. In MIMO-CEM PAS, we send CDM based preambles at the beginning and the end of the transmitted data frame. Channels vectors estimates

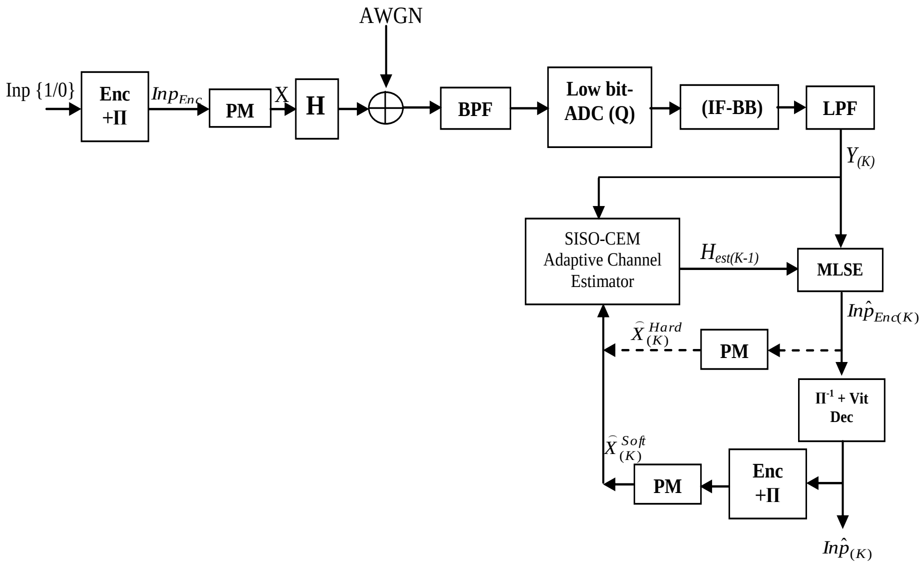

Figure 5. The SISO-CEM (Hard/ Soft) DDCE construction, the dashed line shows DDCE Hard decision path and the solid line shows the Soft decision one.

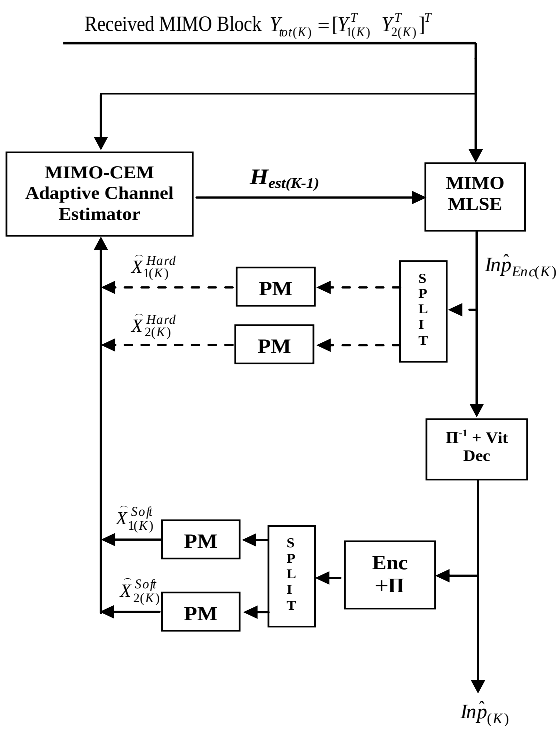

Figure 6. The 2x2 MIMO-CEM (Hard/ Soft) DDCE construction the dashed line shows DDCE Hard decision path and the solid line shows the Soft decision one.

H_{estpq} are estimated at these two points using the correlator and adaptive filter estimators described in Sec.3. Then, linear interpolation is used to estimate the channels H_{estpq} during data part. Figure 8 shows the SISO-CEM PAS channel estimation frame structure. At each pilot position ($X_{(P1)}$, $Y_{(P1)}$) and ($X_{(P2)}$, $Y_{(P2)}$), the channel is estimated using SISO-CEM channel estimator in Sec. 3, then linear interpolation is used to estimate the channel during data part.

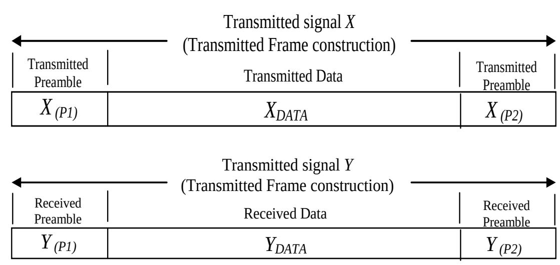

Figure 7. The transmitted and received frame structure of the proposed SISO-CEM PAS channel estimation.

5 PERFORMANCE EVALUATIONS

In this section, we give some BER performance simulations that show the effectiveness of the proposed SISO (MIMO)-CEM block based DDCE in different Doppler frequencies. We evaluate the BER performance of the SISO-CEM DDCE, SISO-CEM PAS and 2x2 MIMO-CEM DDCE.

5.1 Simulation Parameters

In studying SISO (MIMO) – CEM dynamic channel(s) estimator performance, we make use of the simulation parameters shown in Table 1. We use the modified Jack's model (Young's model) presented in [24] to simulate the multipath time varying Rayleigh fading channel. Through our simulations, the BLMS variable step size *u(n)* is adjusted to optimize the adaptive process. Hence, it starts with a certain maximum value u_{max} at the beginning of the adaptive process. Then, it is gradually decreasing for each iteration step *n* until it reaches its minimum value of u_{min} when the number of iterations reaches N_{train}. The decreasing step value u_{step} equals $(u_{max}-u_{min})/N_{train}$. Due to scheme high nonlinearity, u_{max} and u_{min} are adjusted via simulations to ensure fast convergence with minimum number of adaptive iterations N_{train}.

Table 1. Simulation parameters.

Parameter	Value
f_dT_s	0.0001, 0.0002, 0.0005, and 0.001.
Preamble PN sequence length.	1- For DDCE 63 chips for f_dT_s = 0.0001 and 0.0002, and 31 chips for f_dT_s = 0.0005 and 0.001. 2- For PAS 62 chips (divided into parts) for f_dT_s = 0.0001 and 0.0002 and 30 chips for f_dT_s = 0.0005 and 0.001.
Data Block length for DDCE	16 Symbols for f_dT_s = 0.0001 and 0.0002 and 12 symbols for f_dT_s = 0.0005 and 0.001.
B = (Preamble length) / (Total Frame length)	0.14.
Actual Channel model *H*	Multipath time varying Rayleigh fading, equal gain, 4 paths, with RMS delay spread of $\tau_{rms} = 1.12T_s$, T_s is the symbol duration.
Estimated Channel Model H_{est}	4 paths separated by T_s.
ADC quantization bits	1-bit
Sampling rate at ADC	16 fs
BPF	6 order Butterworth, BW = 0.6
FEC Encoder	Convolutional encoder with Constraint length = 7. Rate = ½, *g0 =x7+x5+x4+x2+x1* and *g1=x7+x6+x5+x4+x1*.
FEC Decoder	Hard / Soft input Viterbi Decoder for Hard/ Soft MLSE outputs respectively.
Number of transmit antenna *Mt*	2.
Number of receive antenna *Mr*	2.

5.2 Performance evaluations of the SISO-CEM DDCE

In this section, we evaluate the performance of the proposed SISO-CEM (Hard/Soft) DDCE time varying channel estimator for different f_dT_s values using MSK and GMSK modulations. For comparison, we also give the performance of the SISO-CEM PAS dynamic channel estimator using MSK modulation. In SISO-CEM PAS, soft output MLSE is used. In our evaluations, we only concern about the strictest case of 1-bit ADC because it is considered as the default operation with highest quantization noise. Table 1 shows the simulation parameters used in these evaluations. The normalized preamble size is given as $\left(B = \frac{preamble\ size}{Total\ \ frame\ size} = 0.14 \right)$.

Figures 8-10 show BER performance of MSK based SISO-CEM system with Soft PAS, Hard DDCE, and Soft DDCE respectively. In these figures, perfect means BER performance is evaluated using actual channel information, and estimated means BER performance is evaluated using estimated channel. From these figures, we can notice the superior BER performance of the SISO-CEM Soft DDCE over the other two schemes. SISO-CEM Soft DDCE can track the channel variation even in the too high Doppler frequency of $f_d T_s$ = 0.001 with BER error floor of 0.001. On the other hand, the SISO-CEM Soft DDCE has the highest computational complexity as explained in Sec. 4. Also, the SISO-CEM Soft PAS channel estimation has near SISO-CEM Soft DDCE performance in slow dynamic channels of $f_d T_s$ = 0.0001. The SISO-CEM Hard DDCE has nearly the same BER performance as SISO-CEM Soft PAS channel estimator in the too high Doppler frequency of $f_d T_s$=0.001, but SISO-CEM Soft PAS channel estimator overcomes SISO-CEM Hard DDCE performance in slow and moderate dynamic channel conditions of $f_d T_s$ = 0.0001, 0.0002 and 0.0005.

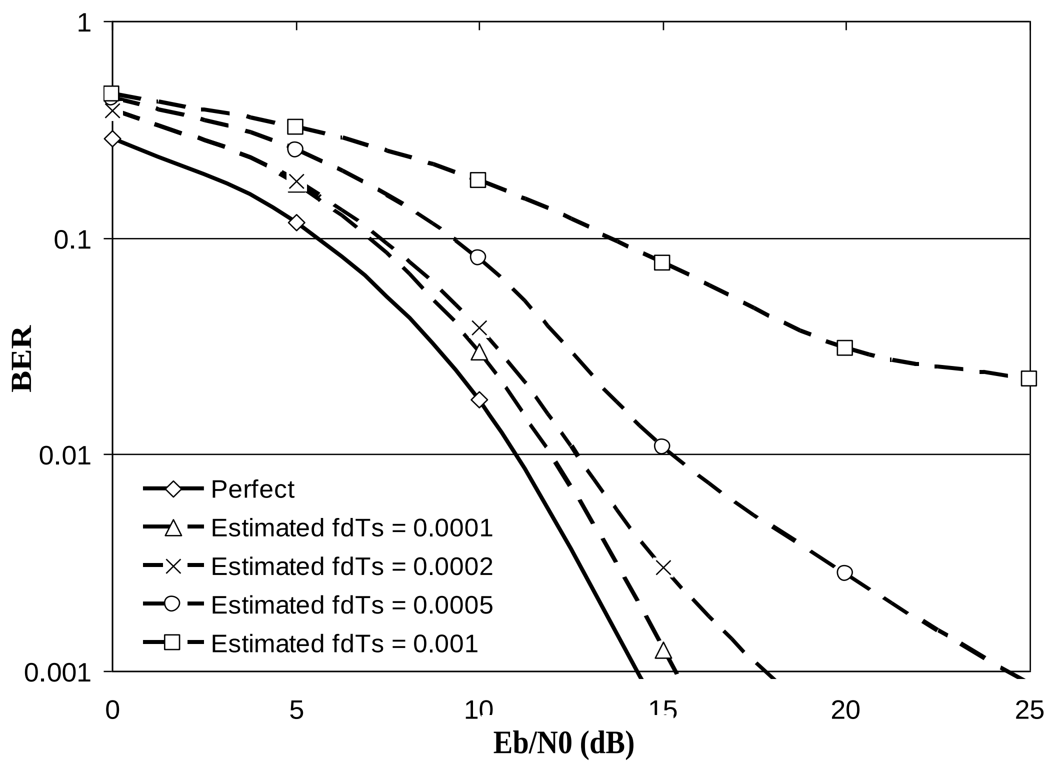

Figure 8. BER performance using Soft decision SISO-CEM PAS channel estimation.

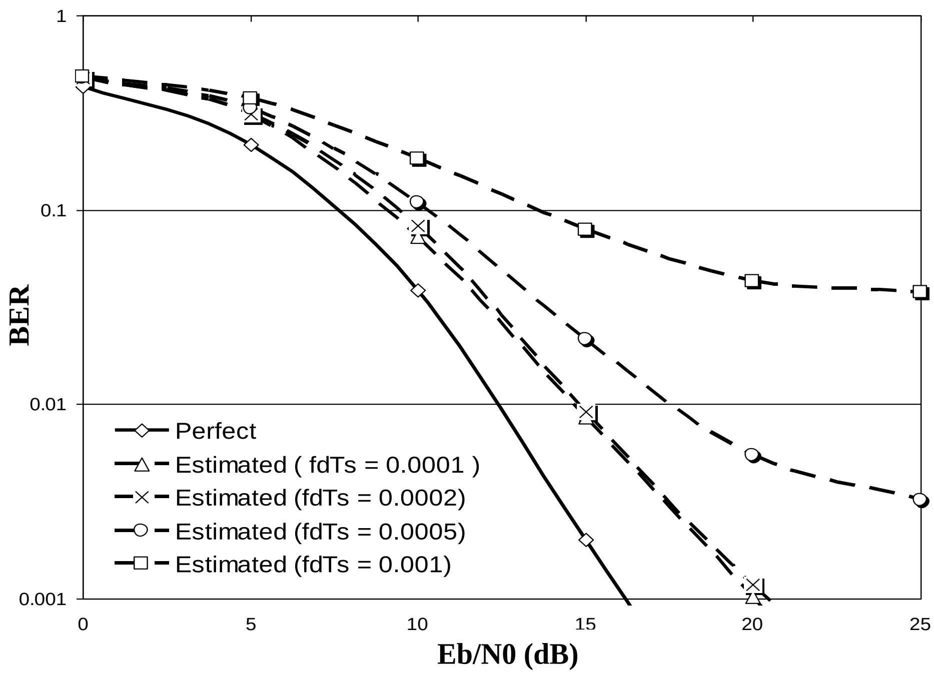

Figure 9. BER performance using Hard decision SISO-CEM DDCE.

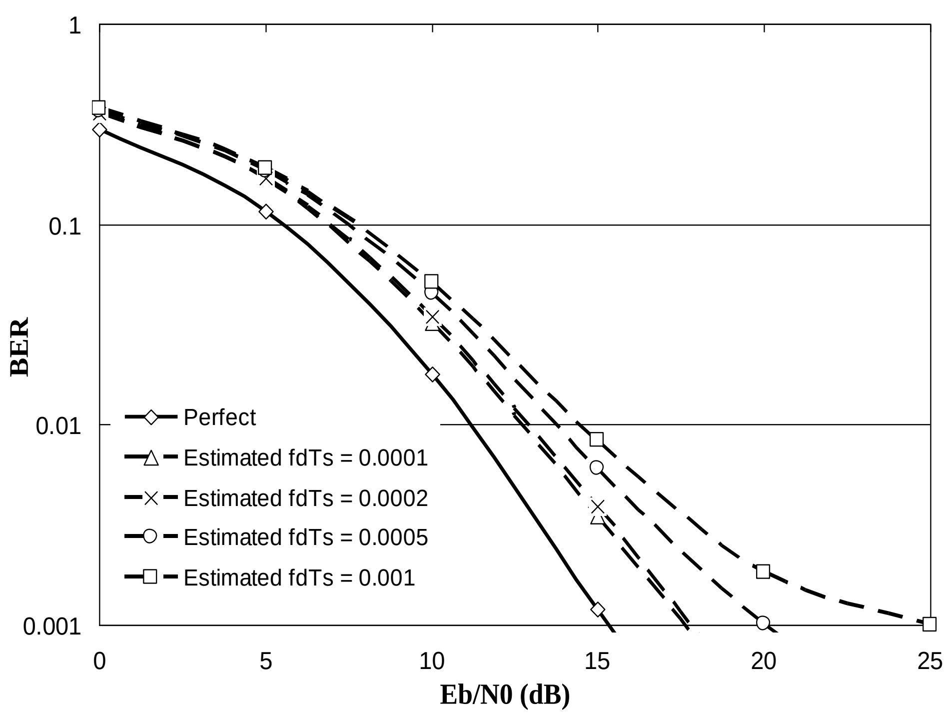

Figure 10. BER performance using Soft decision SISO-CEM DDCE.

But of course, SISO-CEM Hard DDCE BER performance overcomes the performance of SISO-CEM Hard PAS in moderate and high Doppler frequencies as it happens in Soft DDCE and Soft PAS. These figures prove the effectiveness of SISO-CEM (CEM nonlinear MLSE equalizer and adaptive channel estimator) and in general MIMO-CEM systems (explained later) for time varying channel applications.

GMSK modulation is applied to MIMO-CEM system to increase its spectral efficiency [3]. Although higher spectrum efficiency than MSK is achieved using GMSK, it suffers from Inter Symbol Interference (ISI) caused by Gaussian filtering (GF), i.e. there is a tradeoff between spectral efficiency improvement and BER degradation using GMSK. In this section, we test our proposed SISO-CEM Soft DDCE for various GMSK BT values, where BT denotes 3 dB-bandwidth of Gaussian filter normalized by symbol frequency, and for various Doppler frequencies. In these simulations, we utilize the simulation parameters given in Table 1, except we only test SISO-CEM Soft DDCE scheme (because of its superior performance over the other two schemes), and we use GMSK modulation with various BT values of 0.3, 0.5, 0.7 and 1. Another GF is used as the received LPF with BT=1. Figures 11-13 show the simulation results. As shown from these figures, SISO-CEM Soft DDCE works well using GMSK for $f_d T_s$ = 0.0002 and 0.0005, and for BT = 1, 0.7 and 0.5 with no error floor. Although there is no error floor appear until EbN0 = 25 dB for the BT = 0.3 case, there is a big difference between perfect and estimated BER performances, more than 5 dB increase in Eb/N0 is needed to obtain the same BER of 0.01. This value may be

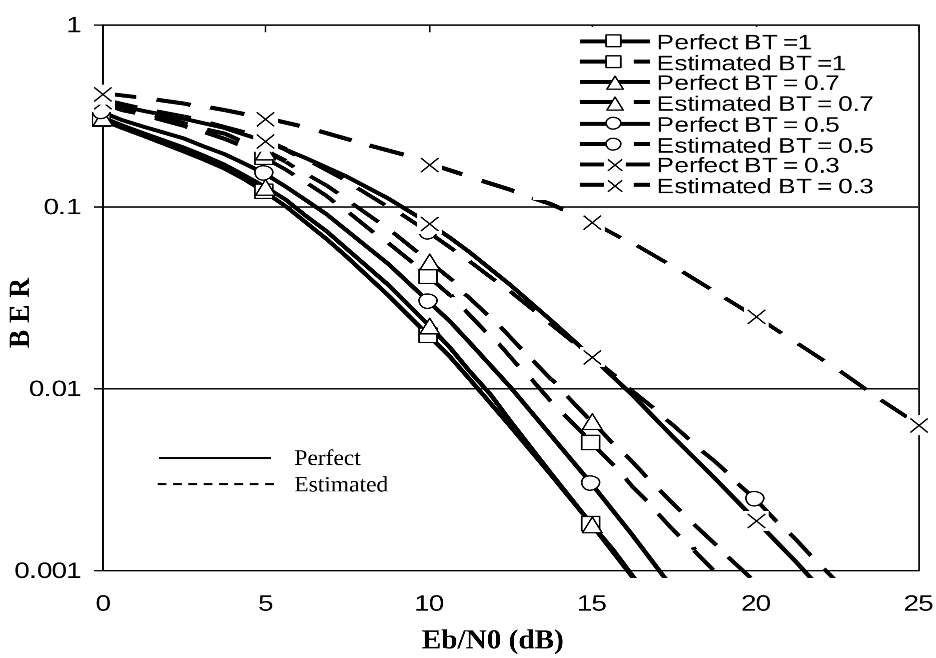

Figure 11 BER performance using SISO-CEM Soft DDCE with $f_d T_s$ = 0.0002.

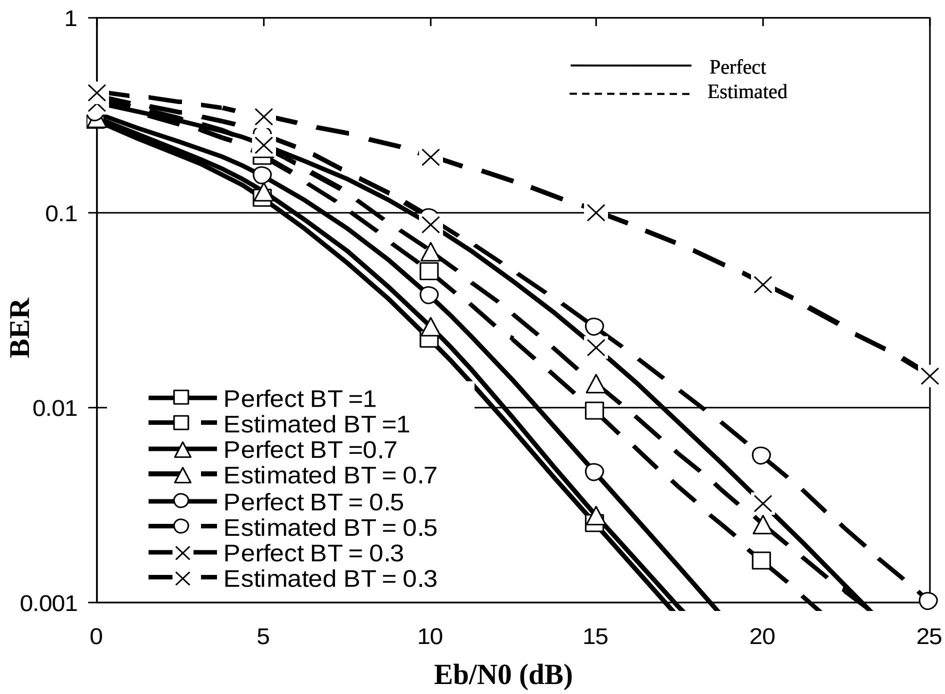

Figure 12 BER performance using SISO-CEM Soft DDCE with $f_d T_s = 0.0005$.

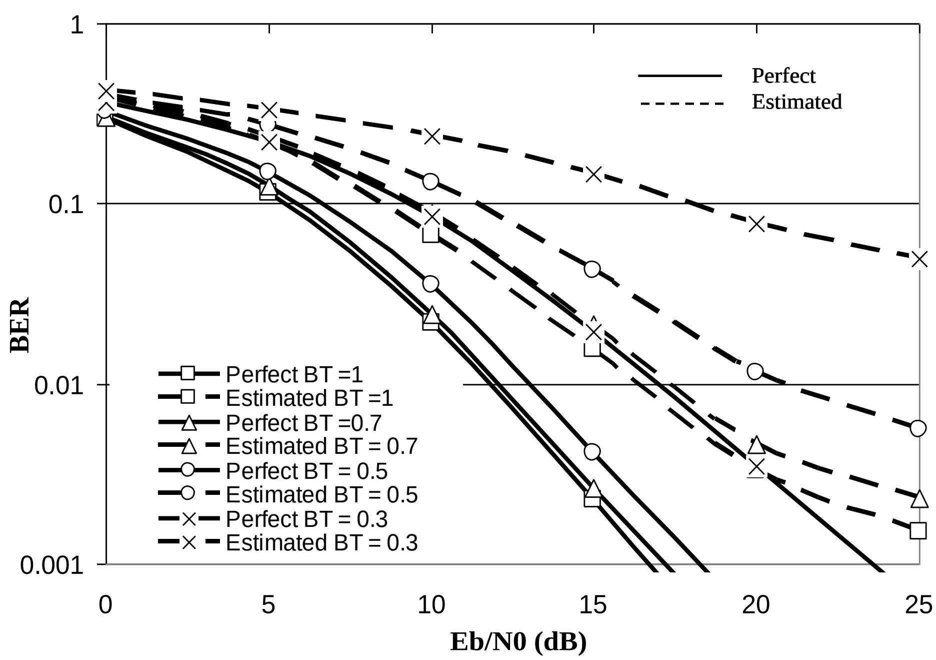

Figure 13 BER performance using SISO-CEM Soft DDCE with $f_d T_s = 0.001$.

increased for higher BER target like BER = 0.001. For the too high Doppler frequency of $f_d T_s$ = 0.001, there is an error floor appear for all BT values, the best performance appear at BT = 1. At BT = 0.3, the estimator performance is highly degraded and far away from the perfect performance.

In conclusion, the performance of the proposed SISO-CEM Soft DDCE is degraded as the Doppler frequency increases and as the GMSK BT value decreases. The worst case occurs at $f_d T_s$ = 0.001 and BT =0.3, which means that the channel estimator needs to track a highly fluctuated channel using a strictly quantized high ISI received preamble signal. For slow and moderate channel variations of $f_d T_s$ = 0.0002 and 0.0005, it is recommended to use GMSK constant envelope modulation with BT = 0.5. And, for the too high channel fluctuation of $f_d T_s$ = 0.001, it is recommended to use BT = 0.7 or 0.5 depending upon the system requirements, i.e., the required performance versus spectral efficiency enhancements.

5.3 Performance Evaluations of the MIMO-CEM DDCE

Because of the superior performance of the Soft DDCE over the Hard DDCE and the conventional Soft PAS method, we test the 2x2 MIMO-CEM Soft DDCE using Table 1 simulation parameters with 2x2 MIMO-CEM configuration shown in Fig. 6. In these simulations, each MIMO channel is 4-path time varying Rayleigh fading with equal gain and RMS delay spread of $\tau_{rms} = 1.12 T_s$ which is estimated by 4 paths with T_s separation channel model. Also, we use soft output MIMO-CEM MLSE equalizer using MSK modulation. Figure 14 shows the BER performance comparisons for different $f_d T_S$ values of 0.0002, 0.0005 and 0.001. Like the SISO-CEM DDCE case, the proposed estimator works well without any error floor for the slow and moderate dynamic channel conditions of 0.0002 and 0.0005, but there is an error floor appear on the too fast time varying channel conditions of 0.001. This figure provides evidence of the effectiveness of MIMO-CEM in dynamic channel applications.

6 Conclusion

In this paper, we have proposed a block based decision directed channel estimation (DDCE) for SISO (MIMO)-CEM systems in time varying channel conditions with high Doppler frequencies. We proved that the proposed (Soft/Hard) DDCE works well in slow time varying conditions and Soft algorithms outperforms Hard ones at the expense of the increased computational complexity. Also, we clarified that linear interpolation PAS and DDCE achieve good channel tracking performance for slow and moderate/high time-varying channels respectively. Also, we evaluated SISO-CEM Soft DDCE using GMSK in presence of large quantization noise attributable to the 1-bit ADC at the receiver side. We recommended to use BT=0.5 for moderate dynamic channels and BT =0.7 or 0.5 for fast one as suitable parameters. At the end of the paper, we presented BER performance of the 2x2 MIMO-CEM Soft DDCE, and we proved its effectiveness even in high Doppler frequency conditions. Future study items are to reduce the computational complexities of the proposed DDCE scheme in MIMO-CEM systems.

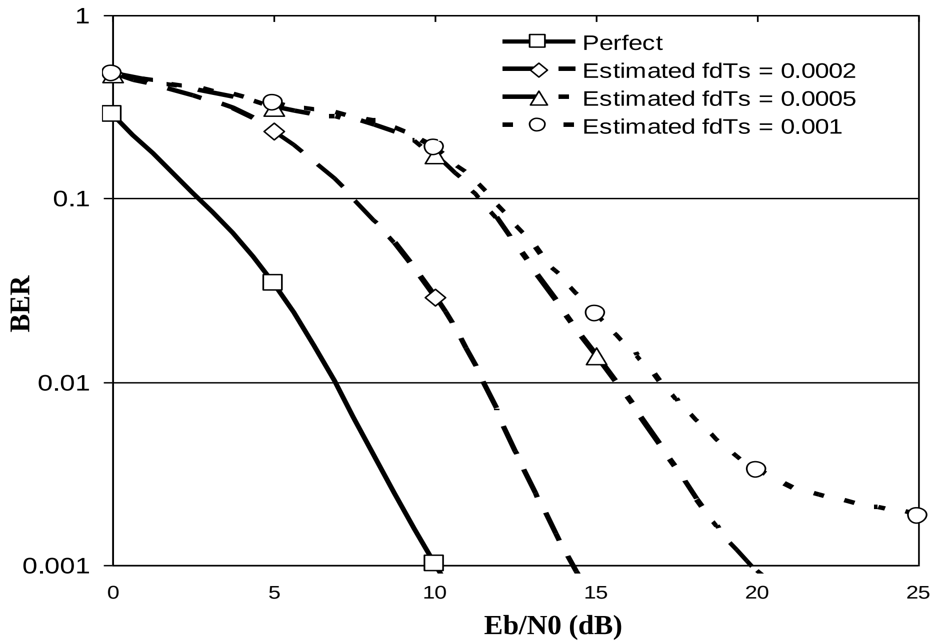

Figure 14. BER performance using Soft Decision 2x2 MIMO-CEM DDCE.

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