Iterative Channel Estimation for Large Scale MIMO with Highly Quantized Measurements in 5G

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***Abstract*—Large-scale MIMO systems offer high spectral efficiency with excellent error performance at low power so long as accurate channel estimates are available. When channel estimation is performed using only pilot signals, undesirably long pilot sequences are needed to achieve the required accuracy. This paper describes an iterative receiver algorithm where detected/decoded data symbols extend the pilot sequences as virtual pilot signals. By using extrinsic feedback, where only information on how the error correction code decoder modifies a posteriori bit probabilities from the detector output is fed back to the channel estimation and detection system, the errors made by the detector and channel estimator do not lead to instability. The proposed system is able to estimate time domain multipath channels with high accuracy. Communications with this system only requires 0.5 dB more power than the system using ideal channel state information, and about 2.5 dB less power than the system that estimates the channel using only the pilot signal. The receiver is also able to operate with coarsely quantized measurements so that low cost receivers can be used at each antenna.**

***Index Terms*—Massive MIMO; Channel estimation; Iterative algorithms; 5G mobile communications**

I. Introduction

Large scale multiple input-multiple output (MIMO) radio communications is an important component of future 5G wireless systems. A large number of sufficiently-spaced receiver antennas results in a large probability of a high quality communications channel from each user's transmitter to the base station [1]. This allows large scale MIMO systems to communicate over random multipath propagation channels with transmission power nearly as low as over ideal additive white Gaussian noise (AWGN) channels. To take advantage of this situation, the receiver requires accurate estimates of radio channel state information (CSI). The signal-to-noise ratio (SNR) at each antenna is equal to the energy-per-bit over noise density, E_b/N_0, multiplied by the number of transmit antennas, T, divided by the number of receive antennas, R. For large scale multi-user MIMO, since $R \gg T$, the SNR is very small for the acceptable E_b/N_0 values. This situation leads to the requirement for a large number of pilot symbols to be used to reach acceptable levels of channel estimation error when standard channel estimation techniques are employed [2], [3]. There are solutions to the channel estimation problem where only a small number of pilots or no pilots are used, known as blind or semi-blind channel estimation [4], [5]. Unfortunately, these techniques either reduce the spectral efficiency of the system, require high SNR values, or require expensive computations at the receiver to jointly estimate the radio channel and the data. In this paper, we propose to solve this problem with the use of iterative channel estimation, where the detected and decoded data signals are used as additional pilot symbols, to reduce the estimation error.

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Iterative channel estimation has been previously demonstrated to provide acceptable communication rates at lower power for large-scale MIMO [6], [7] but the estimation of time-domain multipath radio propagation channels was not considered. In addition we show that this channel estimation can be performed with coarsely quantized measurements including cases where as little as one or two bits of information are obtained from each measurement on the in-phase and quadrature channels. The use of quantization has been considered for large scale MIMO with pilot-based channel estimation in [8]. This paper extends this work by demonstrating that quantized measurements with iterative channel estimation allows for power-efficient communications with a low number of pilots. This is required for low cost receivers with a large number of antennas, since a low cost RF receiver on each antenna will only provide a coarsely quantized low signal-to-noise ratio signal.

Iterative decision-directed channel estimation runs the risk that incorrect decisions made in early iterations can contaminate later iterations performance leading to instability. To avoid this problem, only extrinsic information from the error correction code decoder, information on how the decoder updates the bit probabilities from the symbol detector, is fed back to the channel estimation system instead of the raw output probabilities. This is the same principle used in iterative turbo code decoders. In this case, the principle is used to make the joint channel estimation and symbol detector work efficiently with the decoder. It will be shown that this permits performance within 0.5 dB of power of the ideal case even with coarse quantization.

The remainder of this paper is organized as follows. Section II provides the mathematical model of the large scale MIMO signal. Section III describes the proposed receiver algorithm for joint channel estimation, symbol detection, and error correction code decoding. Section IV will give some results on the use of this algorithm compared with other algorithms under various conditions. Section V will provide some conclusions of this work and possibilities for future work.

II. Signal Model

This paper considers a large-scale uplink MIMO system with T transmitters, with one transmitter per user terminal, and R receiver antennas at the basestation receiver, where $R \gg T$. Large scale uplink MIMO has many channels from each transmitter to the receiver antennas, which is highly likely to permit excellent communication rates at low power [1]. The problem of uplink large-scale MIMO communication addressed here is how the receiver can detect and decode the data sequence sent by each transmit with low hardware, power, and computational costs.

Each transmitter is sending an independent data stream while the basestation receiver is attempting to detect and decode after the signals have been subjected to multipath radio propagation. The transmission format considered here is single-carrier. For each transmitter, the data is split into blocks of N data symbols. A cyclic prefix of CP symbols is appended to the beginning of each block which are copies of the last CP samples transmitted during each respective blocks. The data symbol with index n within block b for transmitter t is denoted as $\mathrm{x}_t\left[n,b\right]$ for $n = 0, 1, \ldots, N-1$ with $b = 1, \ldots, B$. At each receiver, for each block of $N{+}CP$ samples, the cyclic prefix of CP samples is discarded before the signal is processed. The received signal value for time index n at receive antenna r for block b is denoted as $\mathrm{y}_r\left[n,b\right]$:

$$\mathrm{y}_r\left[n,b\right] = \sum_{t=1}^{T}\sum_{l=0}^{L-1} \mathrm{h}_{r,t}\left[l\right]\mathrm{x}_t\left[n-l,b\right] + \mathrm{v}_r\left[n,b\right] \quad (1)$$

where $L-1$ is the longest propagation delay spread in sample periods, $\mathrm{h}_{r,t}\left[l\right]$ is the gain for propagation delay of l sample periods from transmitter t to receiver antenna r, and $\mathrm{v}_r\left[n,b\right]$ is the measurement noise for sample n of block b for receiver antenna r. Because of the cyclic prefix, there is the relationship that $\mathrm{x}_t\left[-l,b\right] = \mathrm{x}_t\left[N-l,b\right]$ for $1 < l < L$ with the standard assumption that $L \le CP$. This makes the regular convolution of $\mathrm{x}_t\left[n,b\right]$ with $\mathrm{h}_{r,t}\left[l\right]$ in Eqn. (1) equivalent to circular convolution permitting frequency domain signal processing. The measurement noise $\mathrm{v}_r\left[n,b\right]$ is assumed to be a circularly symmetric complex Gaussian random variable with zero mean and variance ${\sigma_v}^2$, independent for each receive antenna r, sample index n, and block index b.

The equalization of the radio channel signals is performed in the frequency domains with the Discrete Fourier Transform (DFT) using the well-known Frequency Doman Equalization (FDE) method [9]. We denote the DFT of a time domain signal by capitalization, so:

$$\mathrm{X}_t\left[k,b\right] = \mathcal{DFT}\left\{\mathrm{x}_t\left[n,b\right]\right\} = \sum_{n=0}^{N-1}\mathrm{x}_t\left[n,b\right]\exp\left(-j\frac{2\pi}{N}kn\right) \quad (2)$$

where $j = \sqrt{-1}$ is the imaginary unit, n is the sample index, and $k = 0, \ldots, N-1$ is the frequency bin index. The DFTs are calculated with window lengths of N samples with shorter signals such as $\mathrm{h}_{r,t}\left[l\right]$ being padded with zeros to make vectors of length N.

The DFT of the received signal on antenna r is given as

$$\mathrm{Y}_r\left[k,b\right] = \sum_{t=1}^{T}\mathrm{H}_{r,t}\left[k\right]\mathrm{X}_t\left[k,b\right] + \mathrm{V}_r\left[k,b\right] \quad (3)$$

where $\mathrm{H}_{r,t}\left[k\right]$ is the DFT of $\mathrm{h}_{r,t}\left[l\right]$ taken with respect to propagation delay l, and $\mathrm{V}_r\left[k,b\right]$ is the DFT of signal $\mathrm{v}_r\left[n,b\right]$.

The received signals for all antennas for a given frequency bin k and block b is denoted as $\boldsymbol{Y}_{k,b}$:

$$\boldsymbol{Y}_{k,b} = \boldsymbol{H}_k\boldsymbol{X}_{k,b} + \boldsymbol{V}_{k,b} \text{ where} \quad (4)$$

$$\boldsymbol{H}_k = \begin{bmatrix} \mathrm{H}_{1,1}\left[k,b\right] & \ldots & \mathrm{H}_{1,T}\left[k,b\right] \\ \vdots & \ddots & \vdots \\ \mathrm{H}_{R,1}\left[k,b\right] & \ldots & \mathrm{H}_{R,T}\left[k,b\right] \end{bmatrix} \quad (5)$$

where

$$\boldsymbol{Y}_{k,b} = \left[\mathrm{Y}_1\left[k,b\right], \ldots, \mathrm{Y}_R\left[k,b\right]\right]^T, \quad (6)$$

$$\boldsymbol{V}_{k,b} = \left[\mathrm{V}_1\left[k,b\right], \ldots, \mathrm{V}_R\left[k,b\right]\right]^T, \text{ and} \quad (7)$$

$$\boldsymbol{X}_{k,b} = \left[X_1\left[k,b\right], \ldots, \mathrm{X}_T\left[k,b\right]\right]^T. \quad (8)$$

To support estimation of the radio channel parameters, we find a linear measurement equation for the received signal on antenna r in terms of the channel parameters $\mathrm{h}_{r,t}\left[l\right]$. We define a vector containing the DFTs of the received signal antenna for all blocks $\boldsymbol{Y}_r$ as $\boldsymbol{Y}_r = \left[\mathrm{Y}_r\left[0,1\right], \ldots, \mathrm{Y}_r\left[N-1,1\right], \mathrm{Y}_r\left[0,2\right] \ldots, \mathrm{Y}_r\left[N-1,B\right]\right]^T$. The accompanying noise vector is denoted as $\boldsymbol{V}_r = \left[\mathrm{V}_r\left[0,1\right], \ldots, \mathrm{V}_r\left[N-1,1\right], \mathrm{V}_r\left[0,2\right] \ldots, \mathrm{V}_r\left[N-1,B\right]\right]^T$ The values for the impulse responses from all transmitters to a given receiver r are put into a single vector $\boldsymbol{h}_r$ as below:

$$\boldsymbol{h}_r = \left[\mathrm{h}_{r,1}\left[0\right], \ldots, \mathrm{h}_{r,1}\left[L-1\right], \mathrm{h}_{r,2}\left[0\right], \ldots, \mathrm{h}_{r,T}\left[L-1\right]\right]^T. \quad (9)$$

The vector $\boldsymbol{Y}_r$ can be written as being linearly dependent on the $\boldsymbol{h}_r$ from Eqn. (9):

$$\boldsymbol{Y}_r = \boldsymbol{D}_r\boldsymbol{h}_r + \boldsymbol{V}_r \quad (10)$$

where measurement matrix $\boldsymbol{D}_r$ is defined as

$$\boldsymbol{D}_r = \begin{bmatrix} \mathcal{D}\left\{\boldsymbol{X}_1^1\right\}\boldsymbol{F}_L & \ldots & \mathcal{D}\left\{\boldsymbol{X}_T^1\right\}\boldsymbol{F}_L \\ \vdots & \vdots & \vdots \\ \mathcal{D}\left\{\boldsymbol{X}_1^B\right\}\boldsymbol{F}_L & \ldots & \mathcal{D}\left\{\boldsymbol{X}_T^B\right\}\boldsymbol{F}_L \end{bmatrix}. \quad (11)$$

The $\mathcal{D}\left\{\boldsymbol{U}\right\}$ operator denotes a matrix of all zeros with the exception of the entries of vector $\boldsymbol{U}$ on the main diagonal. The vectors $\boldsymbol{X}_t^b$ for $b = 1, \ldots, B$ and $t = 1, \ldots, T$ contain the DFTs of the transmitted signal in block b from transmitter t:

$$\boldsymbol{X}_t^b = \left[\ \mathrm{X}_t\left[0,b\right], \ldots, \mathrm{X}_t\left[N-1,b\right]\ \right]^T. \quad (12)$$

The N by N matrix $\boldsymbol{F}$ is the so-called Fourier matrix with the entry at row r and column c given by $\exp\left(-j2\pi rc/N\right)$, so the multiplication of a length N vector by $\boldsymbol{F}$ computes the Discrete Fourier Transform of the vector values. The N by L matrix $\boldsymbol{F}_L$ is the sub-matrix of $\boldsymbol{F}$ consisting only of the first L columns. The measurement shown in Eqn. (10) with $\boldsymbol{D}_r$ from Eqn (11) is the computation in the frequency domain of the sum of the convolutions of the impulse responses for each channel with the corresponding transmission sequences.

For initial channel estimation there are P blocks of N symbols which carry pilot signals with values known a priori to the receiver for every B blocks of N symbols which carry data. The pilot measurement equations are given by

$$\boldsymbol{Y}_r^p = \boldsymbol{D}_r^p \boldsymbol{h}_r + \boldsymbol{V}_r^p \text{ with}$$

$$\boldsymbol{D}_r^p = \begin{bmatrix} \mathcal{D}\left\{\boldsymbol{X}_1^{p,1}\right\}\boldsymbol{F}_L & \dots & \mathcal{D}\left\{\boldsymbol{X}_T^{p,1}\right\}\boldsymbol{F}_L \\ \vdots & \vdots & \vdots \\ \mathcal{D}\left\{\boldsymbol{X}_1^{p,P}\right\}\boldsymbol{F}_L & \dots & \mathcal{D}\left\{\boldsymbol{X}_T^{p,P}\right\}\boldsymbol{F}_L \end{bmatrix}. \quad (13)$$

The vector $\boldsymbol{X}_t^{b,p}$ is given by $\boldsymbol{X}_t^{p,b} = \left[\mathrm{X}_t^p[0,b], \dots, \mathrm{X}_t^p[N-1,b]\right]^T$ where $\mathrm{X}_t^p[k,b]$ is the frequency coefficient k for the DFT of the pilot signal from transmitter t for pilot block b and $\boldsymbol{V}_r^p$ is a stacked vector containing the DFT of measurement noises for all pilot blocks for receiver r.

The measurement equations in Eqn. (4), Eqn. (10), and Eqn. (13) form the basis of the data signal estimation and channel estimation equations of Section III.

III. Receiver Algorithm

The architecture of the proposed receiver is shown in Figure 1. The analog circuitry connected to each antenna feeds its signal to an analog-to-digital converter (ADC) which generates quantized samples from Eqn. (1) of the radio signals generated by the transmitters after they have propagated through the environment and after the cyclic prefix from each signal block is discarded. The blocks of signals are converted to the frequency domain with a Fast Fourier Transform (FFT). An iterative algorithm is used in the receiver for joint channel/data estimation. The channel is initially estimated solely from pilot signals to support the initial estimate of the data signal. The estimated data signal is then used as a virtual pilot signal in the following iterations for high accuracy channel estimates supporting higher accuracy data signal estimation. This process is repeated until the data signal converges to a final value. The data estimation algorithm in Subsection III-A. The channel estimation algorithm is described in Subsection III-B.

A. Data Detection/Decoding

The data estimation algorithm uses an estimate of the radio channel frequency response matrices $\boldsymbol{H}_k$ for $k = 0, \dots, N-1$ denoted by $\hat{\boldsymbol{H}}_k$ which are calculated by the channel estimation system. The estimated channel frequency response matrices $\hat{\boldsymbol{H}}_k$ are substituted for the true channel response matrices $\boldsymbol{H}_k \leftarrow \hat{\boldsymbol{H}}_k$ in Eqn. (4) for Frequency Domain Equalization (FDE).

The previous iteration of the data detection/decoding algorithm will provide an estimate of $\boldsymbol{X}_{k,b}$ from Eqn. (8), denoted as $\hat{\boldsymbol{X}}_{k,b}$. For the first iteration, $\hat{\boldsymbol{X}}_{k,b}$ is an all zero vector. The equalized transmitted signal for each frequency bin, $\tilde{\boldsymbol{X}}_{k,b}$, is computed using a standard Zero Forcing (ZF) technique so that

$$\tilde{\boldsymbol{X}}_{k,b} = \left(\hat{\boldsymbol{H}}_k^H \hat{\boldsymbol{H}}_k\right)^{-1} \hat{\boldsymbol{H}}_k^H \left[\boldsymbol{Y}_{k,b} - \hat{\boldsymbol{H}}_k \hat{\boldsymbol{X}}_{k,b}\right] + \hat{\boldsymbol{X}}_{k,b} \quad (14)$$

where superscript H denotes the conjugate transpose operation [1]. The covariance of the estimation error for the zero forcing solution is approximated by

$$\mathrm{Cov}\left(\tilde{\boldsymbol{X}}_{k,b} - \boldsymbol{X}_{k,b}\right) = N\left(\hat{\boldsymbol{H}}_k^H \hat{\boldsymbol{H}}_k\right)^{-1} \hat{\sigma}_v{}^2 \quad (15)$$

where $\hat{\sigma}_v{}^2$ is the modified noise variance. This variance, $\hat{\sigma}_v{}^2$, is increased over the raw measurement noise variance $\sigma_v{}^2$ to model the effect of error in the channel estimation on data estimation with $\hat{\sigma_v}^2 = \sigma_v{}^2 + LT\tilde{\sigma}_h{}^2 S$, where $\tilde{\sigma}_h{}^2$ is the calculated mean channel parameter estimation error from the channel estimation system described in Subsection III-B below, and S is the mean transmitted symbol power. To simplify the noise variance calculation it is assumed that the error for all L taps for each of the T channels to a given receiver are equal. The factor of N in Eqn. (15) comes from the translation in the power from time domain noise signals $\mathrm{v}_r[n,b]$ to their DFTs, $\mathrm{V}_r[k,b]$.

The average of the diagonal elements from Eqn. (15) over all k and b is computed and then divided by N to obtain $\sigma_e{}^2$, which is then used as the variance of the equalized symbol signals in the time domain. For data detection/demodulation, the estimated frequency domain signals $\tilde{\boldsymbol{X}}_{k,b}$ are converted back to the time domain via an Inverse FFT (IFFT) operation to obtain $\tilde{\mathrm{x}}_t[n,b]$. By assuming that the estimation error from the FDE for each symbol is a circularly symmetric complex Gaussian random variable, the probability that a given symbol s_m, from the signal constellation $\mathcal{S} = \{s_0, \dots, s_{M-1}\}$ where M is the modulation order, was transmitted from n from transmitter t in block b can be approximated as

$$\mathrm{p}\left(\tilde{\boldsymbol{x}}_t[n,b]\,|s_m\right) = \frac{1}{\sqrt{\pi\sigma_x{}^2}} \exp\left(-\frac{\left|\tilde{\mathrm{x}}_t[n,b] - s_m\right|^2}{\sigma_x{}^2}\right). \quad (16)$$

Each data bit's probability is specified by a Log-Likelihood Ratio (LLR) value, which is the log of the probability that the given bit has the value zero divided by the probability that the given bit has the value one. A soft-input/soft-output (SISO) maximum a posteriori (MAP) detector is employed to calculate the data bits' LLR values from the previous iteration's decoder output and the symbol probabilities calculated from FDE outputs using Eqn. (16). The SISO MAP detector used in our simulations is supplied by the Coded Modulation Library (CML) [10]. For the first iteration, the decoder prior LLR values are all zeros indicating no prior knowledge of the transmitted data. The extrinsic LLR detector values are forwarded to the decoder stage for the current iteration which is defined as the output LLR values from the detector with the previous iteration's decoder LLR values subtracted out. Extrinsic LLR values indicate how the detector is updating the knowledge of the transmitted data with a zero extrinsic LLR indicating no modification.

We assume that an error correction code is employed at each transmitter where the encoded data bits are interleaved over B data blocks. The decoder stage consists of de-interleaver, SISO decoder, followed by an interleaver. The de-interleaver reorders the LLRs computed by the detector into the order of

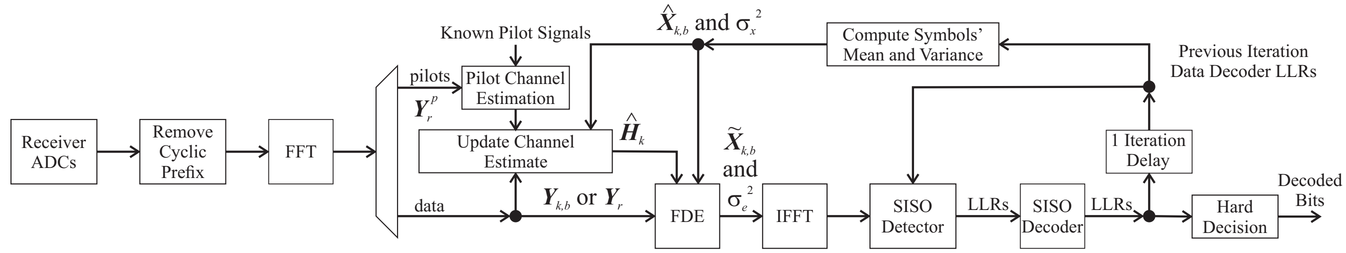

Fig. 1. Receiver Algorithm

the bits at the output to error correction code encoder at the receiver. The SISO decoder computes the LLRs of the encoded bits, which are then reordered by the interleaver into the order of the bits at the input of the modulator in the transmitter. The simulations described in this paper use the BCJR SISO decoder from the CML [10]. The extrinsic output LLR from the decoder is forwarded the following iteration. The extrinsic decoder output LLR is the raw output LLR generated by the decoder with the output LLR from the detector subtracted out.

The output LLRs from the decoders are converted into the probability mass functions for each transmitted symbol, by converting from LLR to bit value probabilities and then summing the appropriate bit probabilities for each symbol index n and block index b to compute the probability for each symbol constellation value s_m for each $\mathrm{x}_t[n, b]$. From these probability mass functions, the mean value and variances of each symbol are computed. The symbol means are converted by a FFT operation into the mean transmitted signals in the frequency domain $\hat{\boldsymbol{X}}_{k,b}$. The symbol variances for all data symbols is averaged to compute the variance of the estimated signals σ_x^2. These values are used in the channel estimation process in the next iteration. If the average absolute difference between the mean symbol values is below a threshold, then the receiver algorithm is assumed to have converged. In this case, a hard decision is performed on the LLR value for the data bits calculated by the decoder and the algorithm is terminated.

It is important that only extrinsic LLR values are forwarded at each stage of the receiver algorithm. Using extrinsic LLR values reduces the probability that incorrect decisions made at either the detector or decoder stage do not reinforce themselves during the next iteration. This is a standard process in iterative signal processing [6], [7], [11].

B. Channel Estimation

Using Linear Minimum Mean Square Error Estimation (MMSE) techniques [12], [13], the measurement Eqn. (13) is used to derive an estimate of $\boldsymbol{h}_r$ from pilot measurement vector $\boldsymbol{Y}_r^p$:

$$\hat{\boldsymbol{h}}_r^p = \sigma_h^2 \left(\boldsymbol{D}_r^p\right)^H \boldsymbol{C}_{yy}^{-1} \boldsymbol{Y}_r \quad \text{where } \boldsymbol{C}_{yy} = \boldsymbol{D}_r \left(\boldsymbol{D}_r^p\right)^H \sigma_h^2 + N\sigma_v^2 \boldsymbol{I}_{NB} \tag{17}$$

where $\boldsymbol{I}_{NB}$ is an identity matrix of order $N \cdot B$ and every entry of $\boldsymbol{h}_r$ is assumed to be an independent and identically distributed circularly symmetric Gaussian random variable with variance σ_h^2. The estimator in Eqn. (17) requires the solution of a linear system of order $N \cdot B$. By using the so-called push-through identity that $\boldsymbol{B}\left(\boldsymbol{AB}+\boldsymbol{I}\right)^{-1} = \left(\boldsymbol{BA}+\boldsymbol{I}\right)^{-1}\boldsymbol{B}$ [14], where $\boldsymbol{A}$ and $\boldsymbol{B}$ are matrices with $\boldsymbol{AB}$ and $\boldsymbol{BA}$ being square matrices and $\boldsymbol{I}$ are appropriately sized identity matrices, then Eqn. (17) is rewritten as

$$\hat{\boldsymbol{h}}_r^p = \sigma_h^2 \left[\left(\boldsymbol{D}_r^p\right)^H \boldsymbol{D}_r^p \sigma_h^2 + N\sigma_v^2 \boldsymbol{I}_{LT}\right)^{-1} \left(\boldsymbol{D}_r^p\right)^H \mathbf{Y}_r^p. \tag{18}$$

The estimator in Eqn. (18) requires a solution of an order $L \cdot T$ system which is much cheaper than that of Eqn. (17). The resulting channel estimation error covariance can be computed using well known techniques to be

$$\mathrm{Cov}\left(\boldsymbol{h}_r - \hat{\boldsymbol{h}}_r^p\right) = \sigma_h^2 \left[\boldsymbol{I}_{LT} - \sigma_h^2 \left(\boldsymbol{D}_r^p\right)^H \boldsymbol{C}_{yy}^{-1} \boldsymbol{D}_r^p\right], \tag{19}$$

where the expectation $\mathrm{E}[\cdot]$ is made with respect to the distribution of the measurements, data signals, and channel parameters. The mean channel estimation error using only pilot signals, $\hat{\sigma}_h^2$, is computed from the average of the channel estimator error over all channel parameters for all receive antennas r from Eqn. (19).

For the second and following iterations, channel estimation is enhanced using the estimated data symbols signals from prior iterations as virtual pilot signals to get better estimates of the channel parameters. First, the difference of the measured signal from the expected signal, given the channel estimate from the pilots, is calculated, $\boldsymbol{Z}_r = \boldsymbol{Y}_r - \boldsymbol{D}_r \hat{\boldsymbol{h}}_r^p$. The channel estimate is computed using an MMSE technique [15] to obtain

$$\hat{\boldsymbol{h}}_r = \hat{\sigma}_h^2 \left(N\tilde{\sigma}_v^2 \boldsymbol{I}_{LT} + \boldsymbol{D}_r^H \boldsymbol{D}_r \hat{\sigma}_h^2\right)^{-1} \boldsymbol{D}_r^H \boldsymbol{Z}_r + \hat{\boldsymbol{h}}_r^p \tag{20}$$

where the $\hat{\sigma}_h^2$ is the channel estimation error from the pilot-only channel estimation technique. The covariance of the channel estimates can be computed using standard techniques as

$$\mathrm{Cov}\left(\boldsymbol{h}_r - \hat{\boldsymbol{h}}_r\right) = \hat{\sigma}_h^2 \left[\boldsymbol{I}_{LT} - \left(\boldsymbol{D}_r^H \boldsymbol{D}_r + N\frac{\tilde{\sigma}_v^2}{\hat{\sigma}_h^2} \boldsymbol{I}_{LT}\right)^{-1} \boldsymbol{D}_r^H \boldsymbol{D}_r\right] \tag{21}$$

where again the $\hat{\sigma}_h^2$ value is the error from the pilot-based channel estimation. In both Eqn. (20) and Eqn. (21), the noise variance considers both the raw measurement noise plus the unknown data signal: $\tilde{\sigma}_v{}^2 = \sigma_v{}^2 + LT\sigma_h{}^2$. The channel estimation error variance value used in the data FDE computation in the current iteration, $\tilde{\sigma}_h{}^2$, is computed from the mean of the diagonal values from Eqn. (21) averaged over all receive antennas r. The values $\hat{\boldsymbol{h}}_r$ and $\hat{\sigma}_h{}^2$ are passed to the Data Detection/Decoding system and the next iteration of the receiver algorithm is started.

Channel estimation must deal with pilot contamination where the errors of two users' channel estimates are increased if their pilot signals are not uncorrelated [3]. The long data signals of different users are highly likely to have very low normalized correlation with each other. Due to this effect, channel estimation from the previously detected data signals, which act as virtual pilot signals in the second and following iterations, are unlikely to suffer from significant pilot contamination effects. This advantage will be further investigated in future work.

IV. Results

To verify the performance of the iterative channel estimation for a large scale uplink MIMO system, we simulate a system with $T = 16$ users communicating with a basestation with $R = 128$ antennas. The users transmit using 4-QAM modulation over $B = 32$ blocks with $N = 256$ samples with a cyclc prefix of $CP = 16$ samples. The radio channels are length $L = 9$ taps with equal mean power on each tap. Initial channel estimation is performed with $P = 2$ pilot blocks with randomly generated pilot signals with the same mean power as the data signals. A standard error correction convolution code of rate $\frac{1}{2}$ with constraint length 7 with generator polynomials $(133, 171)$ expressed in octal is used. The Bit Error Rate (BER) results are shown in Figure 2. It can be seen that the iterative receiver allows for communication power within 0.5 dB of the ideal CSI receiver is available even when coarse 3-bit quantization is used. When the channel is estimated using only pilot signals, almost 3 dB of additional power is required over when iterative channel estimation is employed. The iterative receiver using 3-bit coarse quantization provides almost a 3 dB improvement compared with the pilot-only channel estimation system using ideal quantization The proposed method provides excellent performance when low cost receivers are employed on each antenna and permit communication with low power.

V. Conclusions

The paper presents an iterative receiver algorithm that jointly estimates the transmitted signal while estimating parameters of the multipath propagation channels from the transmitters to the receivers. The iterative receiver is demonstrated to provide good BER performance when a small number of pilots is employed at low transmission power when coarse quantization is used on each antennas' signal. This indicates that the algorithm can provide good performance with low cost hardware making it attractive for commercial deployment in 5G and other future wireless systems. In future work, the performance of this system in the presence of pilot/signal contamination from adjacent networks will be considered.

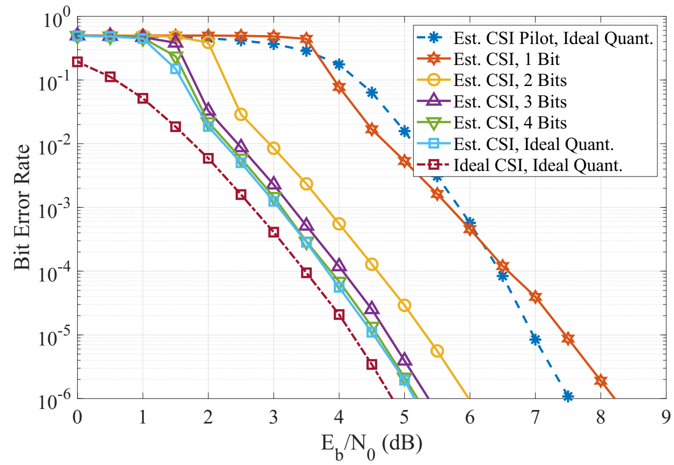

Fig. 2. Results for $T = 16$, $R = 128$, $B = 32$, $P = 2$

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