Experimental Evaluation of Unsupervised Channel Deconvolution for Wireless Multiple-Transmitter/Multiple-Receiver Systems

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Abstract - **In this paper we demonstrate an experimental evaluation of unsupervised (i.e., blind) channel deconvolution that is based on the multi-user kurtosis (MUK) maximization criterion. We focus on the narrowband case and compare the performance of the MUK algorithm against the conventional trained linear MMSE and the V-BLAST algorithm. These results constitute, to the best of our knowledge, the first over-the-air demonstration of blind techniques for multiple-transmitter/multiple-receiver systems.**

1. Introduction

The Bell Labs layered space-time (BLAST) [1] architecture utilizes multi-element antenna arrays at both transmitter and receiver to provide high capacity wireless communications in a rich scattering environment. It has been shown that the theoretical capacity (approximately) increases linearly as the number of antennas is increased [1]. Two types of BLAST realizations have been widely publicized: vertical BLAST (V-BLAST) [2] and diagonal BLAST (D-BLAST). V-BLAST is a simplified version where channel coding is applied to the individual sub-streams, each corresponding to the data stream transmitted by a single antenna. D-BLAST applies coding not only across time, but also across the antennas (sub-streams), and it implies a higher decoding complexity. The transmitter architecture is given in Figure 1. The above algorithms require explicit knowledge of the multiple-input/multiple-output (MIMO) channel response. In the discrete and narrowband case, the response is a complex-entry NxM matrix (where M is the number of transmit and N is the number of receive antennas).

With respect to the receiver knowledge of the channel, an alternative scheme is proposed in [3]. That scheme is based on the multi-user kurtosis (MUK) maximization criterion, and does not require any prior knowledge of the MIMO channel response (i.e., it is blind). The algorithm is proven to be globally convergent to a solution that recovers all sub-streams [3]. A benefit of the blind approach is its improved throughput because a predefined training sequence is no longer needed. The blind receiver may allow application of the multiple-transmitter/multiple-receiver (MTMR) architecture in conventional wireless systems with minimal requirements with respect to changing current system specifications that are originally intended for the conventional single-transmitter/single-receiver architecture.

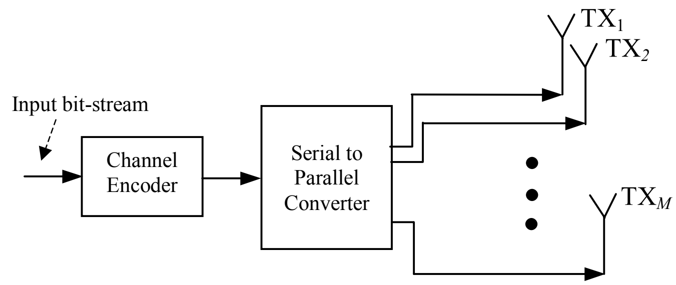

Fig. 1. Transmitter architecture

The focus of this work is to evaluate the performance of this particular scheme with real, *over-the-air* measurements. We have built a MTMR narrowband wireless test-bed that is used for verifications and performance evaluations of different algorithms related to the BLAST wireless communications architecture (e.g., [4, 5]). We observe bit-error rate as a measure of the performance, and we compare the MUK scheme against well-known trained solutions. Performance of the linear MMSE and the uncoded V-BLAST scheme is observed with respect to the size of the predefined training. Furthermore, the tradeoff between performance and improved throughput is analyzed. As shown in the following, the experimental results reaffirm the validity and applicability of the theoretical analysis.

In the following section, we introduce the system model and describe the MUK algorithm. In Section 3, we repeat the basic steps of the V-BLAST receiver algorithm. The features of the narrowband wireless test-bed are given in Section 4. Experimental results are presented in Section 5 and we conclude in Section 6.

2. Multi-user kurtosis algorithm

The baseband received vector is modeled as

$$\mathbf{r}(k) = \mathbf{H}\,\mathbf{a}(k) + \mathbf{n}(k) \qquad (1)$$

$\mathbf{H}$ is a NxM complex-entry matrix that corresponds to the narrowband MIMO channel response. Its column vectors are denoted as $\mathbf{h}_j$ (j = 1, …, M). $\mathbf{a}(k)$ is a complex input (data) Mx1 vector and $\mathbf{n}(k)$ is the Nx1 additive white Gaussian noise (AWGN) impairment, all corresponding to the k^{th} time sample. In order to recover input vector $\mathbf{a}(k)$, $\mathbf{r}(k)$ is filtered by a NxM "spatial equalizer" $\mathbf{W}$ which results in output vector $\mathbf{z}(k)=[z_1(k)\ldots z_M(k)]^T$ as

$$\mathbf{z}(k) = \mathbf{W}^T\,\mathbf{r}(k) = \mathbf{G}^T\,\mathbf{a}(k) + \mathbf{n}'(k) \qquad (2)$$

$\mathbf{G}$ is the MxM global response matrix, $\mathbf{n}'(k) = \mathbf{W}^T\mathbf{n}(k)$ and T denotes transpose. In [3], the proposed multi-user kurtosis (MUK) algorithm is derived from the following optimization criterion

$$\max_{\mathbf{G}} F(\mathbf{G}) = \sum^{M} |K(z_m)| \qquad (3)$$
$$\text{Subject to } \mathbf{G}^H\,\mathbf{G} = \mathbf{I}_M$$

where $K(x) = E(|x|^4) + 2E^2(|x|^2) - |E(x^2)|^2$, is the kurtosis of x, $\mathbf{I}_M$ is the MxM identity matrix and H is Hermitian transpose. The above criterion is previously shown to be driven by a necessary and sufficient condition for perfect source separation in the absence of noise [3]. The MUK algorithm first updates $\mathbf{W}(k)$ in the direction of the the MUK criterion's gradient $K_a = K(\mathbf{a})$ as

$$\mathbf{W}'(k+1)=\mathbf{W}(k) + \mu\ sgn(K_a)\,\mathbf{r}^*(k)\,\mathbf{Z}(k) \qquad (4)$$

where $\mathbf{Z}(k) = [|z_1(k)|^2\ldots|z_M(k)|^2]^T$, and μ is a small step size. Then, a Gram-Schmidt orthogonalization of the columns of $\mathbf{W}'(k+1)$ is performed, resulting in $\mathbf{W}(k+1)$ whose columns are orthogonal (see[3]). Note that before the algorithm is run, the received signal $\mathbf{r}(k)$ needs to be pre-whitened (resulting in a unitary $\mathbf{H}$).

The above algorithm is executed on the data set which has L symbols, and corresponds to a frame which is communicated over the air. All of the symbols are information bearing, i.e., no portion of the frame is dedicated to a training sequence. In order to improve the results of the adaptation in (4) the above algorithm can be re-run several times using the same data set, i.e., the same frame, before the detection of the transmitted data is performed. For the particular implementation of the above algorithm in this paper we apply $\mu = 0.04$. Also, we perform four re-runs to get the matrix $\mathbf{W}$.

3. V-BLAST ALGORITHM

For the sake of completeness, we repeat the basic steps that are executed by the uncoded V-BLAST receiver scheme [2, 4]. In the following, we omit the time index k and we assume that $E(\mathbf{a}\mathbf{a}^H) = \mathbf{I}_M$ (i.e., uncorrelated and unit variance data). The input covariance matrix is

$$\mathbf{R} = E(\mathbf{r}\mathbf{r}^H) = \mathbf{H}\,\mathbf{H}^H + \sigma^2\mathbf{I} \qquad (5)$$

where σ^2 corresponds to the AWGN variance. Power ordering of the sub-streams is required, but for the sake of simplicity, we assume that $|\mathbf{h}_1^2|>\ldots>|\mathbf{h}_M^2|$. The following steps are executed:

1. Reset the counter $p = 1$.

2. Determine the minimum mean square error (MMSE) detector as:

$$\mathbf{m}_p = \mathbf{R}^{-1}\mathbf{h}_p/((\mathbf{R}^{-1}\,\mathbf{h}_p)^H\,\mathbf{h}_p) \qquad (6)$$

3. Perform the MMSE detection as

$$s_p = \mathbf{m}_p^H\,\mathbf{r} \qquad (7)$$

4. Estimate the transmitted data a_p, of the sub-stream p, and cancel its contribution as

$$\mathbf{r} = \mathbf{r} - a_p\,\mathbf{h}_p \qquad (8)$$

5. Deflate the covariance matrix as

$$\mathbf{R} = \mathbf{R} - \sqrt{P/M}\,\mathbf{h}_p\,\mathbf{h}_p^H \qquad (9)$$

   where P is the total transmitted power.

6. Increment $p = p+1$, and repeat steps 2 to 6 if $p < M+1$, i.e., the above steps are performed repeatedly for all sub-streams.

Note that the accuracy of the estimate of the channel response matrix $\mathbf{H}$ is important to the performance of the V-BLAST scheme. In addition, note that V-BLAST is a decision-feedback based algorithm, which may result in error propagation from early detection stages. This effect is stronger in uncoded and low SNR systems. Performance of the algorithm is studied with respect to the length of the training (in number of symbols) that is dedicated to channel estimation, and it is compared with the MUK scheme.

In addition, we compare the performance against the linear MMSE detector. It is derived using (6) and applied as given in (7), but no cancellation (step 4 and 5) of the sub-streams is performed.

4. NARROWBAND MTMR WIRELESS TEST-BED

Let us now briefly describe the hardware components of the narrowband MTMR wireless test-bed. The radio frequency (RF) front-end of the test-bed consists of an antenna array, and the corresponding array of analog RF transmitters and receivers. The carrier is at 1.95GHz and the signal bandwidth is limited to 30KHz. The baseband digital signal processing is executed using a DSP multiprocessor system: Pentek 4285 [6]. It consists of eight Texas Instrument's TMS320C40 DSPs, offering a total processing power of 400MIPS. The interfacing towards the baseband is realized using a system of multi-channel A/D (Pentek 4275 [7]) and D/A (Pentek 4253 [8]) converters, respectively. The maximum sampling rate per baseband channel is 100KHz.

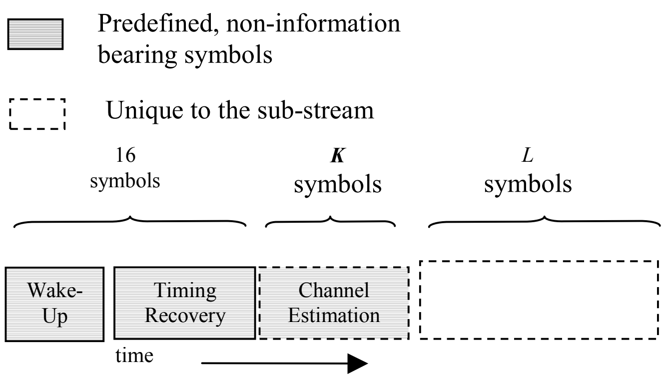

Fig. 2. Frame Structure

5. Experimental Results

We present results that correspond to non-line-of-site indoor over-the-air trials. We could use up to 8 transmit and 8 receive antennas, but here we present results for M=4 transmit and N=6 receive antennas.

In this particular experiment, we use the QPSK modulation format, transmitting 25Ksym/sec on each sub-stream (i.e., per antenna). This modulation format is known to be the most favorable in the case of the MUK algorithm (note that this property is also known for the constant-modulus algorithms [9]). No forward error correction coding is used. The symbols are organized as follows (see Figure 2). Symbols 1 to 16 are used for synchronization, i.e., frame and symbol timing recovery. Note this part of the frame is identical for all sub-streams. K symbols compose a training sequence, which is used for estimation of the MIMO channel response. Between the sub-streams, the sequences are mutually orthogonal and with the equal transmit power. This part of the frame is used by the trained receivers, only. It is not used in the case of the MUK, thus increasing its effective throughput. L symbols are information-bearing symbols.

For the trained receivers we observe the performance for training lengths K=10, 20, 30 and 40 symbols. The frame length is set to L=100 or 200 symbols, i.e., 4 or 8msec respectively. The channel estimation is performed at the beginning of the frame, and no channel tracking is executed latter, i.e., it is assumed that the channel is static during the frame period. This assumption is valid for the indoor MIMO channels (mostly pedestrian speeds). The MUK adaptive algorithm uses all 100 or 200 symbols for the adaptation and, as stated earlier, it does not use the training sequence (K_{muk} = 0).

In Figures 3 and 4, we present the eye diagram per sub-stream. We also present the squared error between z_p (output of the MUK algorithm for L = 200) and transmitted data a_p (i.e., transmitted data, p =1, …, 4), after the outputs are properly re-ordered. The figures correspond to the re-run stage 1 and 4 respectively. From the results we observe the ability of the MUK scheme to perform channel deconvolution and source separation (by opening the constellation eye). Also, we note that the performance is improved with the higher number of iterations and re-runs.

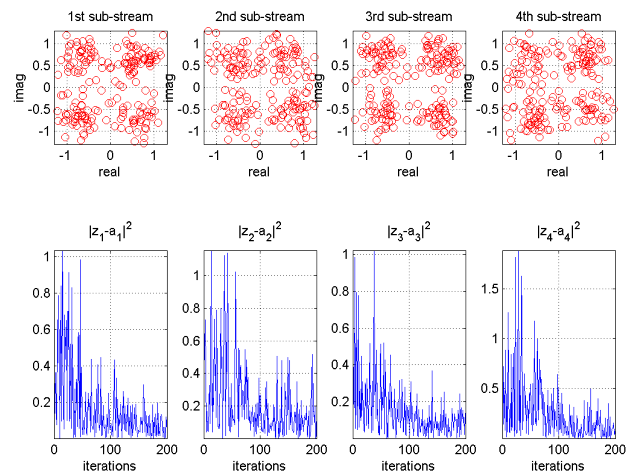

Fig. 3. The eye diagram, and the square error per sub-stream, after the first re-run (L=200, 4x6, over-the-air trials, SNR~12dB.)

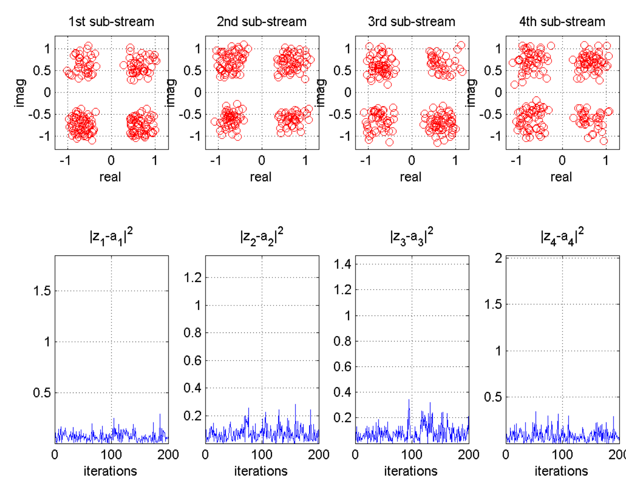

Fig. 4. The eye diagram, and the square error per sub-stream, after the fourth re-run (L=200, 4x6, over-the-air trials, SNR~12dB.)

Figure 5 presents the CDF of the bit-error rate estimate (BER, measured per frame) obtained from over-the-air indoor trials. Measured SNR is approximately 12dB. From the results, it is obvious that the MUK does not fail in the case of the real communication session. The trained receivers do perform better, but the MUK is able to follow the performance of the linear MMSE detector. Note that the MUK increases the throughput by 20% (for L=100 and K=20) and/or 10% (for L=100 and K=10), at the price of higher BER. We have run the system for lower SNR's. Both linear solutions (MUK and MMSE) outperformed the uncoded V-BLAST receiver at SNR's below 2dB. Figure 6 depicts the mean BER of the receivers versus the length of the training sequence K. Performance of the MUK is not affected by the value K because it does not use any training.

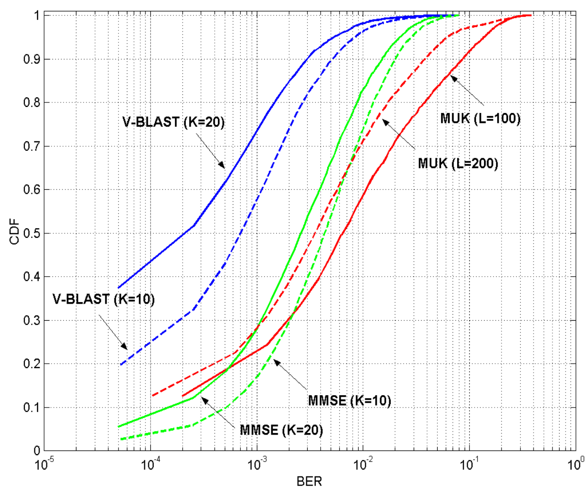

Fig. 5. CDF of BER, M=4, N=6, indoor over-the-air trials, SNR~12dB.

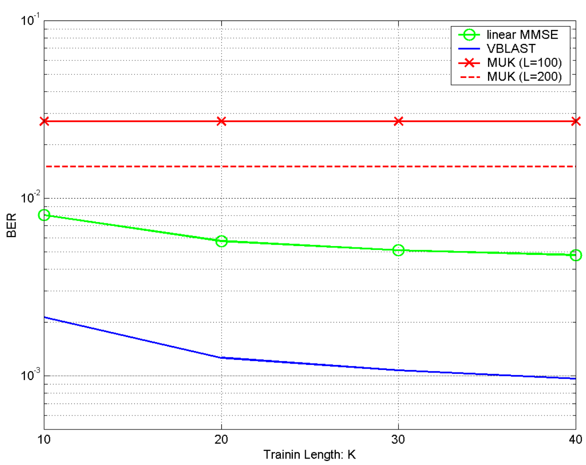

Fig. 6. BER vs. Training length K=10…40, L=100, M=4, N=6, indoor over- the-air trials.

6. Conclusion

In this paper, we confirm the validity of the previously reported theoretical performance of the MUK algorithm in an over-the-air wireless MIMO environment. This study is believed to be, to the best of our knowledge, the first over-the-air demonstration of a blind source separation algorithm. It turns out that the MUK algorithm performs successfully and approaches closely the performance of the MMSE solution. It is hence our belief that blind approaches can be successfully used in MIMO wireless systems.

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