# Media-Based MIMO: Outperforming Known Limits in Wireless

Ehsan Seifi, Mehran Atamanesh and Amir K. Khandani
E&CE Department, University of Waterloo,
Waterloo, ON, Canada

***Abstract*—The idea of Media-based Modulation (MBM), introduced in [1] [2], is based on embedding information in the variations of the transmission media (channel states). MBM offers several advantages vs. legacy systems, including "additivity of information over multiple receive antennas", and "inherent diversity over a static fading channel". MBM is particularly suitable for transmitting high data rates using a single transmit and multiple receive antennas. However, complexity issues limit the amount of data that can be embedded in channel states using a single transmit unit. To address this shortcoming, the current article introduces the idea of Layered Multiple Input-Multiple Output Media-Based Modulation (LMIMO-MBM). LMIMO-MBM enables forming a high-rate constellation as superposition of constituent vectors due to separate transmit units. Relying on such a layered structure, LMIMO-MBM can significantly reduce both hardware and algorithmic complexities, as well as the training overhead. Simulation results show excellent performance in terms of Symbol Error Rate (SER) vs. Signal-to-Noise Ratio ($SNR$). For example, a $4 \times 16$ LMIMO-MBM is capable of transmitting $32$ bits of information per (complex) channel-use, with SER $10^{-5}$ at $E\ /N_0 \simeq -3.5$dB (or SER $10^{-4}$ at $E\ /N_0 = -4.5$dB). This performance is achieved using a single transmission (no extension in time/frequency), and without adding any redundancy for Forward-Error-Correction (FEC). Application of FEC can further improve the performance. For example, applying Reed-Solomon codes enables transmitting $30$ bits of information per (complex) channel-use with a Frame Error Rate (FER) $10^{-5}$ at $E\ /N_0 \simeq -6$dB. Under a set of mild conditions, by applying FEC with error correction capability $t$, the slope of the error rate vs. $SNR$ (with hard decision decoding) will asymptotically increase by a factor of $t+1$.**

## I. Introduction

Three issues limit the performace of Multiple-Input Multiple-Output (MIMO) antenna systems . First, the problem of deep fades can be only (partially) alleviated, but only at the cost of a reduction in the achievable rate, or so-called Multiplexing Gain (MG) [7]. Second, MG increases only with the smaller of the number of transmit and receive antennas. Third, the MIMO channel matrix is typically non-orthogonal, reducing the achievable rate as compared to an orthogonal channel matrix. Media-based Modulation (MBM) deals with these three issues.

MBM can be interpreted as creating a channel with a finite number of, say $M$, states. MBM transmitter selects one of these $M$ states in each transmission, and thereby, can transmit $\log_2(M)$ bits of information. This can be realized by perturbing the propagation environment in the vicinity of transmit antenna(s), which in turn will change the overall transmission path. Transmitter will then send a signal through the selected channel state, in order to convey the particular selection to the receiver. The process is such that the corresponding received signal acts as a unique signature for the selected channel state. This means, in the absence of noise, the received signal would uniquely determine the channel state. In the case of multi-path fading with rich scattering, each channel state results in a point over the receiver dimensions, and such points have independent, identically distributed (i.i.d.) Gaussian components. A key point is that, if $K$ receive antennas are used, the number of complex receive dimensions will increase by $K$, while satisfying the i.i.d. property for the distribution of points over all the resulting coordinates. This means, constellation points will span the entire space formed over receiver $K$ spatial dimensions. This phenomenon occurs even if a single antenna is used for transmission. This is in contrast to the traditional MIMO where the effective dimensionality is governed by the minimum of the number of transmit and receive antennas. The task of decoding at the receiver concerns mapping the signtuare signal, received in noise, to the corresponding channel state. In MBM, the cardinality of the set of input signals is typically one, although one can embed further information by selecting the input signal from a set with a larger cardinality. This corresponds to combining MBM with legacy transmission systems (called Source-Based Modulation, SBM, hereafter).

**Example:** Consider a wireless channel with two states $s_1$ and $s_2$. In one of the states, the channel gain is equal to 0.5, and in the other state, it is equal to 1.5. Transmitter can select either of the two states in each transmission, but does not know which state corresponds to which gain value. Let us assume we are interested in transmitting two bits per channel use. In one scenario, reminiscent of SBM, the transmitter selects one of the two states for all its transmissions and use it with a Pulse-Amplitude-Modulation (PAM) constellation of size 4, composed of points $\{-3, -1, 1, 3\}$. With probability $1/2$, the selected channel state corresponds to the one with the lower gain, resulting in the received constellation $\mathcal{C}_1 = \{-3/2, -1/2, 1/2, 3/2\}$ with a $d_{\min} = 1$. This means one can guarantee a wrost case $d\min$ equal to 1 using an average transmit energy of $(9+1+1+9)/4 = 5$. In a second scenario, reminiscent of MBM, for each transmission, transmitter uses one bit of information to select the channel state, and transmits a Binary-Phase-Shift-Keying (BPSK) modulation with points $\{-1, 1\}$. It easily follows that the receiver will observe a 4-PAM constellation with points $\mathcal{C}_2 = \{-3/2, -1/2, 1/2, 3/2\}$, again resulting in $d_{\min} = 1$, but this time at the cost of using one unit of energy vs. the 5 units used in the first scenario. The underlying assumption is that, although transmitter is oblivious to the actual realization of the channel gain, receiver is aware of the structure of the constellation and its labeling. This information can be easily conveyed to the receiver through an initial training phase, in which the transmitter selects the two channel states in an order that is prearranged with the receiver. For example, it is mutually agreed to use $s_1$ in the first training period, and $s_2$ in the second one, or vice versa. It is also agreed that the state used in the first training symbol represents data bit zero and the second one represents data bit one, or vice versa.

The above example shows another notable property. If the channel state is changed randomly from transmission to transmission, the equivalent channel can become Ergodic in time (corresponding to constellation $\mathcal{C}_2$ in this example). As a consequence, the inherent bottleneck occurring in the case of SBM, corresponding to being stuck with the worse channel state in all transmissions, is avoided. This phenomenon is further discussed in later parts of the current article and is interpreted as an inherent (built-in) diversity effect. Reference [2] shows that, this phenomenon will asymptotically (for large constellation sizes) convert a static fading channel into an (Ergodic) AWGN channel. The important point is that in MBM, this so-called built-in diversity is inherently (automatically) realized at no cost, in particular without wasting rate or energy. This is unlike traditional MIMO systems where an increase in the diversity order is unavoidably accompanied by a reduction in rate (MG). ■

### A. Literature Survery

Reference [1] shows that embedding part or all of the information in the (intentional) variations of the transmission media (channel states) can offer significant performance gains vs. traditional Single-Input Single-Output (SISO), Single-Input Multiple-Output (SIMO) and Multiple-Input Multiple-Output (MIMO) systems. This method, coined in [1] as Media-Based Modulation (MBM), is in contrast with traditional wireless systems where data is embedded in the variations of an RF source (prior to the transmit antenna) to propagate via fixed propagation paths (media) to the destination. In particular, using capacity arguments, reference [1] shows that by using a single transmit antenna and a single or multiple receive antennas, MBM can significantly outperform SBM.

Following [1], reference [2] proves that, a $1 \times K$ MBM over a static multi-path channel with rich scattering asymptotically achieves the capacity of $K$ (complex) AWGN channels, where for each unit of energy over the single transmit antenna, the effective energy for each of the $K$ AWGN channels is the statistical average of channel fading. In addition, the rate of convergence is computed. It is shown that significant gains can be realized even in a SISO-MBM setup. An example for the practical realization of the system using RF mirrors, accompanied with realistic RF and ray tracing simulations, are presented. Issues of equalization and selection gain are also briefly discussed.

The idea of embedding information in the state of a communications channel is not new. MachZehnder modulators, widely used for signalling over fiber, modify the light beam after leaving the laser. However, due to the lack of multipath in single mode fibers, the advantages due to SIMO-MBM and MIMO-MBM, realized in the context of wireless, do not apply.

In distant relationship to MBM, there have been some recent works on embedding data in antenna beam-patterns [8]-[10] or antenna selection [11]-[15]. Note that unlike MBM, none of these works can realize advantages due to embedding information in the channel state. Most notably, these advantages, reported for the first time in [1] [2], include "additivity of information over multiple receive antennas" and "inherent diversity without sacrificing transmission rate".

In [8] [9], data is embedded in two orthogonal antenna beam-patterns, which can transmit a binary signal set. Although use of orthogonal basis is common in various formulations involving communications systems, it usually does not bring any benefits on its own, it just simplifies problem formulation and signal detection by keeping the noise projections uncorrelated. This means there are no clear advantages in designing the RF front-end to support orthogonal patterns as used in [8] [9]. The motivation in [8] [9] is to reduce the number of transmit chains and no other benefits are discussed.

Bains [10] discusses using parasitic elements for data modulation, and shows limited energy saving, which again is due to the effect of classical RF beam-forming.

Spatial Modulation (SM) [11]-[15] uses multiple transmit antennas with a single RF chain, where a single transmit antenna is selected according to the input data (the rest of the data modulates the signal transmitted through the selected antenna). SM is in essence a diagonal space-time code, where the trade-off between diversity and multiplexing gain has been in favour of the latter. A shortcoming of SM is that the rate due to the spatial portion increases with $\log_2$ of the number of antennas, while in MBM, it increases linearly with the number of RF mirrors (on-off RF mirrors are introduced in [2] as means of embedding binary data in channel states). In SM, antennas should be sufficiently separated to have independent fading, while in MBM, RF mirrors are placed side by side. The switches used in SM are high power, which means expensive/slow, or each antenna needs a separate Power Amplifier (PA) with switches placed before PAs. The switches used for RF mirrors in MBM are cheap, low power and fast.

The use of tuneable parasitic elements external to the antenna(s) for the purpose of RF beam-forming is well established. However, the objective in traditional RF beam-forming is "to focus/steer the energy beam, which does not realize the advantages of MBM (where data is modulated by tuning external parasitic elements).

In continuation to SM [11]- [15], Space-Shift Keying (SSK) [16]-[18] and Generalized SSK (GSSK) [19] have been studied for low-complexity implementation of MIMO systems. Again, the key motivation behind the application SM/SSK/GSSK in [11]-[19] is the use of a single RF chain, and accordingly, one antenna remains active during data transmission. Other advantages are mentioned as avoiding inter-antenna synchronization and removing inter-channel interference [18]. In addition to complexity considerations, it is shown that these modulation schemes may offer better error performance as compared to conventional MIMO techniques [16].

The advantages of MBM, which are discussed in details in [1][2], are briefly explained next.

### B. Advantages of MBM

MBM offers an inherent diversity in dealing with static fading. Since constellation points in MBM correspond to different channel realizations, the spacing among points is formed using different channel gains. Hence, both good (high gain) and bad (low gain) channel conditions contribute towards forming the required spacing among constellation points. This feature of MBM removes the bottleneck of deep fades in static fading channels without compromising the rate. It was shown that significant gains can be realized even in a SISO-MBM setup due to inherent diversity [1].

In $1 \times K$ SIMO-MBM, due to the independence of channel gains to different receive antennas, the received signal constellation spans all the $Q = 2 \times K$ receive dimensions. Therefore, MBM benefits from larger spacing among constellation points in case of using multiple receive antennas. This is analogous to additivity of information over multiple receive antennas. This is in contrast to SIMO-SBM where the received signal spans a single complex dimension, and consequently, only $SNR$ gains can be achieved through techniques such as maximum ratio combining (without increasing the effective signal space dimensionality). In addition, a desirable feature of MBM is that the constellation points are spread across the signal space following a Gaussian distribution, which is in agreement with Gaussian random coding requirements. Relying on this feature, [2] shows that a $1\times K$ MBM over a static multi-path fading channel asymptotically achieves the capacity of $K$ parallel (complex) AWGN channels, where for each unit of energy over the single transmit antenna, the effective energy for each of the $K$ AWGN channels is the statistical average of the channel fading.

Another benefit of SIMO-MBM is the "$K$ times energy harvesting" which means, assuming $K$ receive antennas and a fading with statistical average gain of one, the average received signal energy is $K$ times the transmit energy. Legacy MIMO systems enjoy a similar property, however, in the case of MIMO systems, the channel matrix is typically non-orthogonal. This results in correlation among noise components along different receive dimensions if channel inversion is used at the receiver. Eigen beam-forming can be used to diagonalize the channel matrix, but the underlying issue will surface in another equivalent form; it results in different channel gains along different eigen-dimensions. In contrast, in MBM, noise components are added at different receive antennas and are independent of each other and have equal variances. This results in equal $SNR$ for all the underlying parallel channels, and increases the capacity as compared to legacy MIMO. Readers are referred to [1] for further discussions.

Some complexity issues arise when only a single RF transmit unit is used to realize the advantages of MBM at high data rates. Next section discusses the underlying practical issues, and present methods to address them.

### C. Limitations of SIMO-MBM in Transmitting High Rates

Using a single transmit unit to embed all the information in channel states will limit the amount of information that can be practically transmitted per channel-use. For example, let us assume we are interested to transmit 32 bits of information per channel-use. The complexity in using a single RF transmit unit to encode all 32 bits may be excessive. The reasons are: (1) It is practically difficult to use 32 RF mirrors in a single RF transmit unit. (2) Training requires transmitting $2^{32}$ test signals, which is resource intensive and is vulnerable to channel time variations. (3) Detection requires searching (minimum distance decoding) among $2^{32}$ signal points, resulting in excessive algorithmic and storage complexities. (4) To deal with channel time variations, it is of interest to track the changes in the position of the constellation points in order to increase the minimum time interval between successive training phases. It is difficult to track $2^{32}$ constellation points.

### D. Proposed Solution

To address the above issues, this article proposes a new method to perturb the RF channel, resulting in a layered constellation structure. Assume several separate transmitter units, each generating a set of received vectors (called "constituent vectors" hereafter), operate at the same time. As a result, the received vector will be the sum of the constituent vectors corresponding to different transmit units. As the constituent vectors are random and independent from each other, the cardinality of the set of received vectors will be (with high probability) equal to the product of the cardinalities of the set of constituent vectors corresponding to different transmit units. As a result, using $R_n$ RF mirrors at $N$ transmit units (each unit has a single radiating element) results in $2^{N\times R_n}$ received vectors, capable of transmitting $R = N \times R_n$ bits of information per channel-use. Transmit units are arranged such that there is a negligible coupling among them. As a result, constellation points will be formed as the sum (superposition) of constituent vectors due to each transmit unit. To emphasize this superposition property, which forms the basis behind the complexity reduction, the proposed approach is called Layered MIMO-MBM, or LMIMO-MBM, hereafter. Benefits of this setup in reducing complexity are as follows: (1) Number of RF mirrors used at individual transmit units is reduced by a factor of $N$. (2) Detection is performed using an iterative search algorithm. At each step, the proposed algorithm searches for the constituent vector contributed by a given transmit unit (initializing the search by zero vectors) and continues iteratively. To improve the search result, one can start from multiple initial points (for example, corresponding to different permutations of transmit units) and at the end select the best candidate. (3) Training is simplified as it is composed of $N$ separate training tasks, each over a smaller set of alphabet size $2^{R_n}$, as compared to training over $2^{N\times R_n}$ elements. (4) Tracking is simplified as it is composed of $N$ separate tracking tasks, each over a smaller set of alphabet size $2^{R_n}$ elements, as compared to tracking $2^{N\times R_n}$ elements.

For example, to send 32 bits of data per channel-use, one can use 4 transmit units each modulating 8 bits, which means only 8 on-off RF mirrors are required in each transmit unit. Training/tracking is composed of 4 separate tasks, each involving a small alphabet size of $2^8 = 256$ elements.

A disadvantage of the LMIMO-MBM method proposed in the current article is that the received constellation vectors do not correspond to independent Gaussian vectors any longer as the constellation vectors are summation of a smaller number of independent constituent (Gaussian) vectors. This is in contrast with the requirement of Gaussian random coding over AWGN channels. However, the corresponding degradation in $SNR$ performance is negligible. For example, Figure 1 demonstrates an example for this gap when minimum distance decoding is performed using exhaustive search.

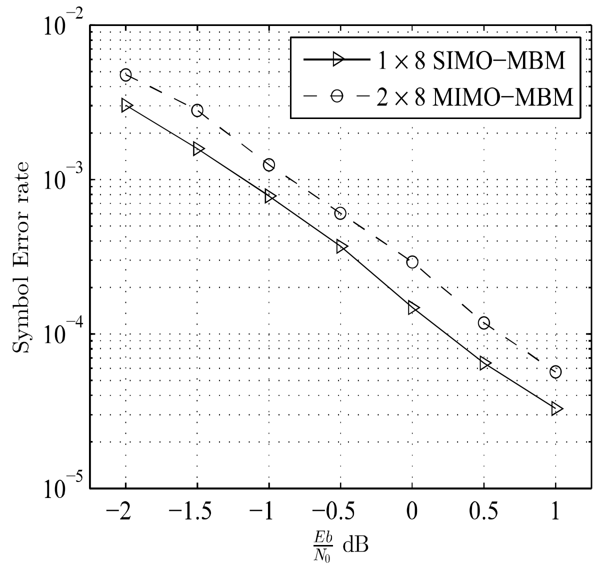


Fig. 1: Performance of the 2×8 LMIMO-MBM (2 RF mirrors are used in each transmit unit) vs. 1×8 SIMO-MBM (4 RF mirrors are used in a single transmit unit), $R = 16$ bits per channel-use for a single transmission in time (without any FEC).

## II. System Model

In a $N \times K$ Layered MIMO-MBM (LMIMO-MBM) system (see Figure 2), the $M$ messages to be sent are distributed among $N$ transmit units, using vector $\mathbf{m}$ with components $m_1, ..., m_N$. Subsequently, each transmit unit selects its own channel realization vector $\mathbf{h}^n(m_n), n = 1, ..., N$, according to $m_n$. These channel realization vectors, called constituent vectors, add to form the received constellation points $\mathbf{c}(\mathbf{m})$. Again, $\mid h_k^n(m_n) \mid^2 = 1$, $\forall m$, $\forall n$ and $\forall k$. Similar to SIMO-MBM, each transmit unit can send optional SBM information bits. To attain this, transmit unit $n, n = 1, ..., N$, modulates its own RF signal based on the $n$th component of the information vector $\mathbf{s}$, to generate RF modulated signal $\mathbf{S}_n(s_n), n = 1, ..., N$. Due to symmetry, distributing rate and power equally among individual transmit units results in the highest end to end mutual information. Throughout the paper, we assume power/rate is equal among transmit units. Consequently, the sets of LMIMO-MBM constituent vectors, corresponding to different transmit units, are of equal cardinalities, namely $\sqrt[N]{M} = 2^{R_m/N} = 2^{R_n}$. Assuming: (1) unit power for each transmit unit, and (2) linear modulation for the SBM part, the received signal will be equal to:

$$\mathbf{c}(\mathbf{m}) = \sum_{n=1}^{N} s_n \mathbf{h}^n(m_n), \tag{1}$$

where $\mathbf{c}(\mathbf{m})$ is the received constellation point with $K$ complex dimensions. This means constellation points are formed as a weighted superposition of constituent vectors due to each transmit unit. For a Rayleigh fading channel, elements of channel realization vectors $h_k^n(m_n)$ are i.i.d. complex Gaussian. However, the received constellation vectors are no longer independent. Again, to simplify presentation, the dependency on SBM message is ignored in what follows. As a result, 1 is simplified to: $\mathbf{c}(\mathbf{m}) = \sum_{n=1}^{N} \mathbf{h}^n(m_n)$.

## III. Benefits of LMIMO-MBM

Using multiple transmit units simplifies receiver training and signal detection, specifically in transmitting large amounts of information per channel-use. Although MBM transmitter is oblivious to the details of the constellation structure, receiver training is required to convey the constellation structure to the receiver side. Training complexity grows linearly with the size of the constellation, making it an expensive task for constellations of large cardinalities. When using multiple transmit units in LMIMO-MBM, constellation set is formed by superposition of smaller sets of size $\sqrt[N]{M}$. Therefore, one can measure $h_k^n(m_n)$ $\forall n, \forall k$ and $\forall m$, by sending pilot signals (using

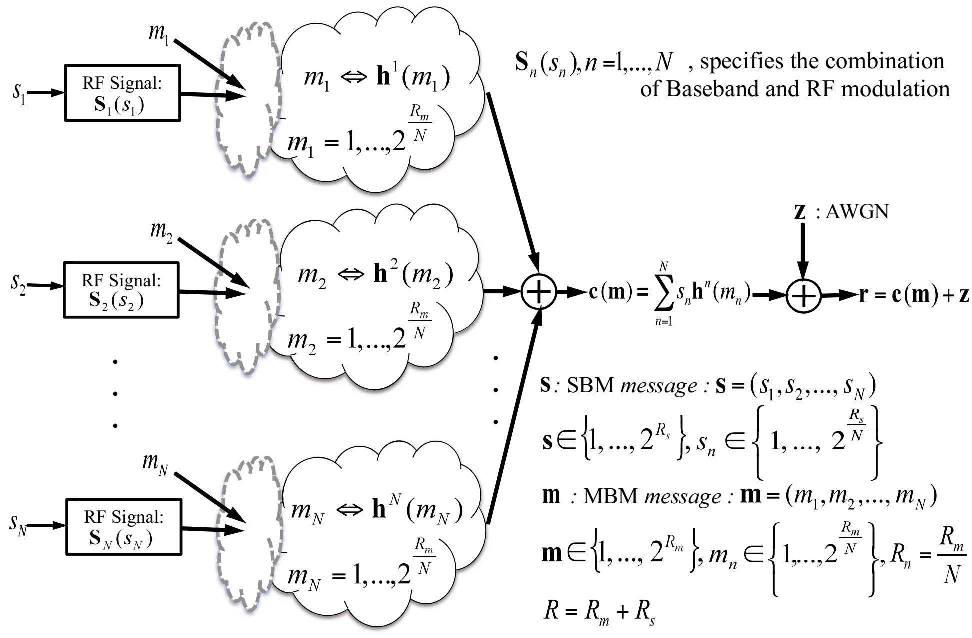


Fig. 2: LMIMO-MBM block diagram (assuming linear modulation for SMB data).

one transmit unit at a time) and then constructing the entire constellation at the receive side by using superposition property (captured in equation (1)). This means complexity of the receiver training will reduce from $\mathcal{O}(M)$ to $\mathcal{O}(N \times \sqrt[N]{M})$. Furthermore, there would be no need for huge memory to save all the constellation points $\mathbf{c}$, since on demand computation can take place, provided that constituent vectors $\mathbf{h}^n$ are known at the receive side. Another benefit is the reduction in the complexity of signal detection by exploiting the structure of the constellation due to its layered construction. In this article, this benefit is realized using a (greedy/sub-optimum) iterative search algorithm, which searches among $\sqrt[N]{M}$ constituent vectors at each iteration. In the proposed LMIMO-MBM, the dependency among constellation points results in a small decrease in the end-to-end mutual information, as compared to using random constellations, i.e., a constellation with i.i.d. Gaussian distribution for the components of the constellation points (resembling random Gaussian code-books). However, the performance degradation remains negligible (for example, see Figure 1).

## IV. Detection Algorithm

A fast greedy iterative algorithm, enabled by layered structure of the proposed MIMO-MBM, is used for sub-optimal minimum distance signal detection. Advantages of the proposed algorithm include: (1) The complexity grows as $\mathcal{O}(\sqrt[N]{M})$ compared to $\mathcal{O}(M)$ in linear search. (2) The complexity grows linearly with the number of dimensions in contrast to the alternative search mechanisms known in the literature of NNS. (3) The algorithm does not require any storage space more than what is required to store channel realizations (constituent vectors) for the individual transmit units, which is of order $\mathcal{O}(N \times \sqrt[N]{M})$. (4) There is no need for preprocessing, in contrast to alternative search mechanisms known in the literature of Nearest Neighbor Search (NNS).

**Iterations**: Algorithm 1 is the pseudocode for the proposed sub-optimum minimum distance detection in LMIMO-MBM. Each iteration is composed of $N$ greedy steps. At each step, the algorithm attempts to (successively) find the constituent vector corresponding to a single transmit unit. At step $i$, a potential solution $\hat{\mathbf{c}}^{(i)}$, for the minimum distance vector to the query signal $\mathbf{r}$ is given as the current best solution. Suppose $\hat{\mathbf{c}}^{(i)}$ is formed by superposition of constituent vectors $(\hat{\mathbf{h}}^1, ..., \hat{\mathbf{h}}^N)$. The algorithm compares the constituent vector corresponding to transmit unit $i$, which means $\hat{\mathbf{h}}^i$, with all other vectors in the set $\mathcal{H}^i = \{\mathbf{h}^i(1), ..., \mathbf{h}^i(2^{R_n})\}$ of constituent vectors corresponding to transmit unit $i$. Subsequently, $\hat{\mathbf{h}}^i$ is replaced with the vector $\tilde{\mathbf{h}}^i$ in $\mathcal{H}^i$ that results in a constellation point $\hat{\mathbf{c}}^{(i+1)}$, which (among all choices available at this step) is the closest to the signal $\mathbf{r}$. Therefore,

$$\tilde{\mathbf{h}}^i = \underset{\in \mathcal{H}^i}{\text{argmin}} | \; \mathbf{r} - (\hat{\mathbf{c}}^{(i)} - \hat{\mathbf{h}}^i + \mathbf{h}) \; |_2 \qquad (2)$$

$$\hat{\mathbf{c}}^{(i+1)} = \hat{\mathbf{c}}^{(i)} - \hat{\mathbf{h}}^i + \tilde{\mathbf{h}}^i. \qquad (3)$$

In other words, at each step, a search over constituent vectors corresponding to a single transmit unit is performed (based on the current knowledge of signals of the other transmit units). Each iteration is composed of $N$ such steps, and in total $T$ iterations are performed before concluding the search. Upon completion of each iteration, $\hat{\mathbf{c}}^{(N+1)}$ is passed to the next iteration as the current best candidate, i.e., closest to the query signal $\mathbf{r}$. As can be seen in (2), there is no need to store all constellation points, since they can be computed on the fly using constituent vectors.

**Initialization**: At the first step of the first iteration, there is no prior knowledge of any of the constituent vectors. Therefore, $\hat{\mathbf{c}}^{(1)}$ is initialized to a vector of all zero elements, which in fact is not a valid constellation point. At the end of the first iteration (i.e., after $N$ steps), $\hat{\mathbf{c}}^{(N+1)}$ will be a valid constellation point.

**Improving the Search**: The algorithm in its simple form explained above can find the optimum solution in vast majority of cases. However, since we are dealing with very low error rates, even a small number of errors due to the algorithmic failure (e.g. iterations end-up in a loop) can govern the performance and result in error floor. Simulation results show that, given a received signal $\mathbf{r}$, the decoded constellation point may be different when different orderings of transmit units for (successive) decoding are considered. For this reason, multiple runs of the above algorithm, corresponding to different permutations of transmit units, is used to improve the search. Each of these runs correspond to one of $N!$ possible permutations of the sequence $(1, ..., N)$, corresponding to a different ordering of transmit units in successive decoding.

The performance can be further improved by using multiple (i.e $P > 1$) candidate points in each run. This means at step $i$, given $P$ best points as the current solution, the algorithm replaces the $i$th constituent vector in each of these $P$ points with constituent vectors in the set $\mathcal{H}^i$, and updates the set of the best $P$ points for the next step (or next iteration). Larger values for $P$ increases the chance of finding the nearest point to $\mathbf{r}$.

## V. Simulation Setup

For the simulation of the proposed LMIMO-MBM system, the constituent vectors corresponding to each transmit unit are generated with complex i.i.d. Gaussian random components of unit variance, and then their linear combination is used to form the constellation. The performance is averaged over many independent runs. $E_b$, energy per bit, is defined as the sum of signal energies of transmit units divided by the total number of bits per transmission, and $N_0$ is the AWGN spectral density at individual receive antennas. Therefore, $E_b/N_0 = NE/RN_0 = E_s/RN_0$, where $E$ is the signal energy corresponding to each transmit unit, and $E_s$ is the total transmit energy per constellation point.

Figure 3 shows the SER performance for $4\times16$ LMIMO-MBM, over a static Rayleigh fading channel with AWGN, transmitting 32 bits of raw data per channel use. Detection is concluded after two iterations (over 4 transmit units), using $P = 128$ candidate points and considering different permutations of transmit units. Note that the performance shown in Figure 3 is over a single transmission, without using any FEC. In the absence of FEC, signal detection can be performed with the lowest possible delay of a single symbol. These features of "lowest possible decoding delay" and "small error probability over a single time transmission" simplify the use of methods based on decision feedback (there will be no error propagation effects), for example for the purpose of equalization and/or tracking the constellation structure in time.

**Algorithm 1** Iterative detection algorithm

Search for the nearest (Euclidean distance) constellation point to received signal $\mathbf{r}$

**function** FIND($\mathbf{r}$)
  $\hat{\mathbf{c}}^{(N+1)} = \mathbf{0}$
  **for** $j = 1, ..., T$ **do** ▷ $j$ is the loop index for iterations
    $\hat{\mathbf{c}}^{(1)} = \hat{\mathbf{c}}^{(N+1)}$
    **for** $i = 1, ..., N$ **do** ▷ $i$ is the loop index for steps
      $\tilde{\mathbf{h}}^i = \underset{\in\mathcal{H}^i}{\text{argmin}} |\ \mathbf{r} - (\hat{\mathbf{c}}^{(i)} - \hat{\mathbf{h}}^i + \mathbf{h})\ |_2$
      $\hat{\mathbf{c}}^{(i+1)} = \hat{\mathbf{c}}^{(i)} - \hat{\mathbf{h}}^i + \tilde{\mathbf{h}}^i$
    **end for**
  **end for**
  **return** $\hat{\mathbf{c}}^{(N+1)}$ ▷ nearest point
**end function**

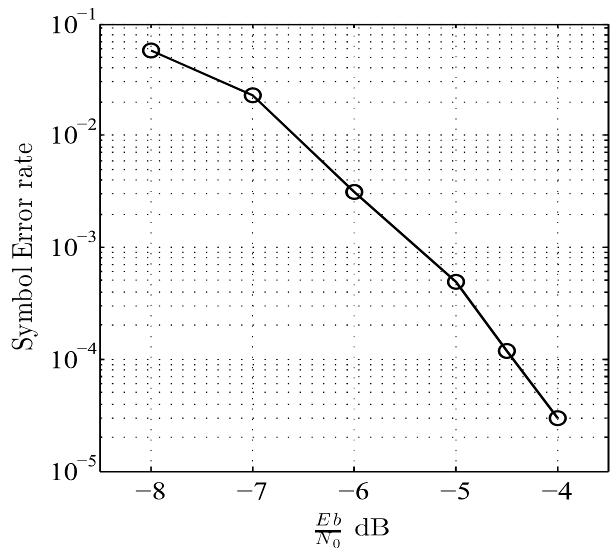


Fig. 3: Performance of $4\times16$ MIMO-MBM for a single transmission (without any FEC), $R = 32$ bits per channel-use, detection is performed using Algorithm 1 with different permutations of transmit units with $P = 128, T = 2$.

## VI. Application of Forward Error Correction

In the application of FEC to MBM, it is beneficial to consider coding schemes that operate on MBM symbols.

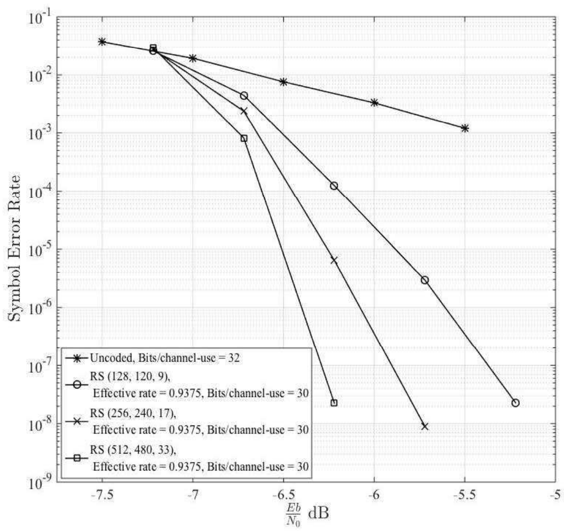


Fig. 4: Performance of 4×16 MIMO-MBM, uncoded vs. Reed-Solomon code.

Class of Group codes with alphabet size $M$ would be a natural choice. Reference [20] proves that in searching for good group codes, one can limit the search to those formed over elementary abelian groups. Maximum Distance Separable (MDS) codes, including Reed-Solomon codes, are a subclass of such group codes for which the minimum distance $d_{\min}$ has the maximum possible value satisfying the Singleton bound. As a result, a natural choice in the application of FEC to MBM would be the class of Reed-Solomon codes with alphabet size $M$ and block length $M-1$. Reed-Solomon codes used in this article are obtained by puncturing such a larger code. Using such a Reed-Solomon code of block size $L$ and dimension $D$ with minimum distance $d_{\min}$ results in an error correction capability of $t = \left\lfloor \frac{d_{min}-1}{2} \right\rfloor$. Figure 4 shows the performance in the application of Reed-Solomon codes with symbols corresponding to MBM constellation points. Reference [21] shows that by applying such a coding scheme in conjunction with hard decision decoding, the slope of the error rate vs. $SNR$ will asymptotically increase by a factor of $t+1$. Consequently, application of FEC will realize an effect similar to "diversity over time" with a diversity order determined by $t+1$. Note that, unlike random-like codes such as Turbo-code and Low Density Parity (LDPC) codes which typically suffer from error floor, the slope of the error curve in coded MBM will not change as $SNR$ increases.

Due to space limitations, readers are referred to [21] for discussions regarding MBM potential bandwidth increase, issues of decision feedback and channel training, as well as a practical (small size and low complexity) RF configuration for embedding information in channel states.

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