Recent advances in MIMO wireless systems

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Abstract

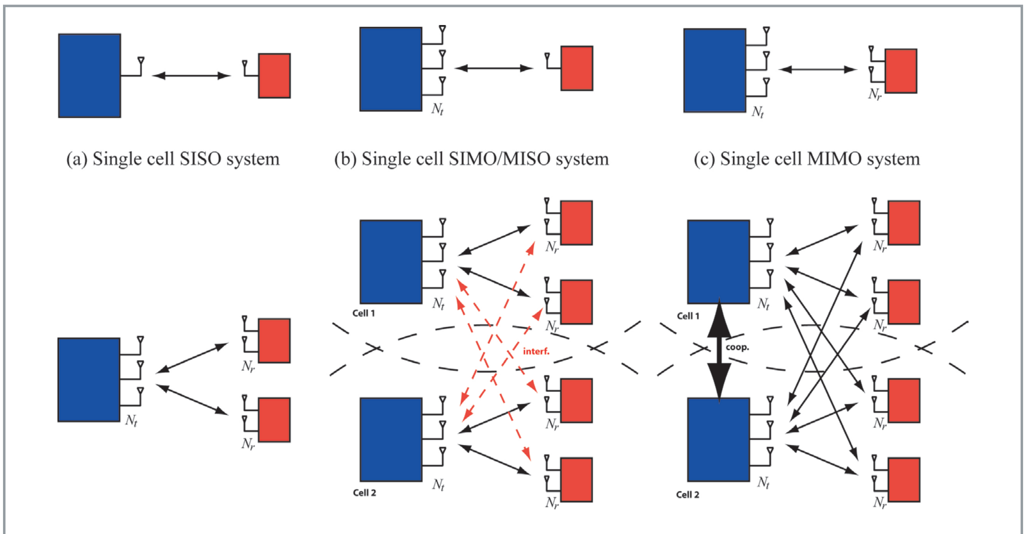
In the next years, one of the most significant technological developments that will lead to the new broadband wireless generation is the communication via Multiple-Input Multiple-Output (MIMO) systems. MIMO systems are known to provide an increase of the maximum rate, reliability and coverage of current wireless communications, without additional bandwidth or transmit power. For these reasons, one of the research lines at the iTEAM research Institute is focused on this kind of wireless systems. This paper presents an overview of MIMO wireless techniques, highlighting the aspects of them where our research is mainly concentrated. Especially, the problems of efficient detection in point to point MIMO systems and beamforming in coordinated MU-MIMO systems are discussed. Finally, some of the solutions to these problems that have been carried out at the iTEAM are addressed.

Keywords: MIMO systems, MIMO detection, coordinated MU-MIMO

1. Introduction

In the next years, one of the most significant technological developments that will lead to the new broadband wireless generation is the communication via Multiple-Input Multiple-Output (MIMO) systems [1]. MIMO systems are known to provide an increase of the maximum rate, reliability and coverage of current wireless communications, without additional bandwidth or transmit power. MIMO systems have already been employed in the existing 802.11n and 802.16e standards resulting in a huge leap in achievable rates.

The evolution of MIMO wireless communication, from Single Input Single Output (SISO) systems to multi-cell coordinated multi-user MIMO (MU-MIMO) systems is shown in Fig. 1. The first system (Fig. 1(a)) depicts the classical and easiest way of communication, using one transmitting and one receiving antenna. Its capacity is only limited by the signal-to-noise ratio (SNR). Fig. 1(b) shows a system where either transmitter or receiver has several antennas. Smart antennas, which use arrays of antennas, are examples of these sys-



(a) Single cell SISO system
(b) Single cell SIMO/MISO system
(c) Single cell MIMO system
(d) Single cell MU-MIMO
(e) Multi-cell MU-MIMO
(f) Multi-cell coordinated MU-MIMO

Figure 1. *MIMO systems evolution*

The basic aim of MIMO systems is to exploit the spatial dimension, due to multiple antennas in transmitter and receiver side, as well as the temporal dimension.

tems and improve performance regarding coverage, capacity or quality of the radio link. The main techniques used by these systems are beamforming and spatial diversity, which can achieve a logarithmic increase in spectral efficiency.

A point-to-point or single-user MIMO (SU-MIMO) is shown in Fig. 1(c). In this system, both transmitter and receiver have several antennas, N_t and N_r, respectively. The basic aim of MIMO systems is to exploit the spatial dimension, due to multiple antennas in transmitter and receiver side, as well as temporal dimension. MIMO can be subdivided into three main categories: precoding, spatial multiplexing, and diversity coding.

- **Precoding** is multi-layer beamforming in a narrow sense or all spatial processing at the transmitter in a wide-sense. In (single-layer) beamforming, the same signal is emitted from each of the transmit antennas with appropriate phase (and sometimes gain) weighting such that the signal power is maximized at the receiver input. The benefits of beamforming are to increase the signal gain from constructive combining and to reduce the multipath fading effect. In the absence of scattering, beamforming results in a well defined directional pattern, but in typical cellular conventional beams are not a good analogy. When the receiver has multiple antennas, the transmit beamforming cannot simultaneously maximize the signal level at all of the receive antenna and precoding is used.

- **Spatial multiplexing** requires MIMO antenna configuration. In spatial multiplexing, a high rate signal is split into multiple lower rate streams and each stream is transmitted from different transmit antennas in the same frequency channel. If these signals arrive at the receiver antenna array with sufficiently different spatial signatures, the receiver can separate these streams, creating parallel channels for free. Spatial multiplexing is a very powerful technique for increasing channel capacity at higher Signal to Noise Ratio (SNR). The maximum number of spatial streams is limited by the lesser in the number of antennas at the transmitter or receiver. Spatial multiplexing can be used with or without transmit channel knowledge. In our research group, we are dealing with the problem of finding efficient detection schemes for spatial multiplexing SU-MIMO systems (see Fig. 1(c)), under the assumption of perfect channel knowledge.

- **Diversity coding** techniques are used when there is no channel knowledge at the transmitter. In diversity methods a single stream (unlike multiple streams in spatial multiplexing) is transmitted, but the signal is coded using techniques called space-time coding. The signal is emitted from each of the transmit antennas using certain principles of full or near orthogonal coding. Diversity exploits the independent fading in the multiple antenna links to enhance signal diversity. Because there is no channel knowledge, there is no beamforming or array gain from diversity coding.

Spatial multiplexing can also be combined with precoding when the channel is known at the transmitter or combined with diversity coding when decoding reliability is in trade-off. Foschini [2] and Telatar [3] have shown that the channel capacity for a MIMO system can be increased as the number of antennas is increased under some conditions, proportional to the minimum number of transmit and receive antennas. Spatial multiplexing techniques make the receivers very complex, and therefore it is typically combined with Orthogonal frequency-division multiplexing (OFDM) or with Orthogonal Frequency Division Multiple Access (OFDMA) modulation, where the problems created by multi-path channel are handled efficiently.

The use of MIMO systems was traditionally intended for point to point communication. The natural extension of this original system would be to consider MIMO in multi user scenario. The vision for next generation cellular networks includes data rates approaching 100Mbps for highly mobile users and up to 1Gbps for low mobile or stationary users, which requires efficient use of the available spectrum. Multi user MIMO (MU-MIMO) technology is expected to play a key role in this context. There are two challenges in MU-MIMO scenario (Fig. 1(d)): uplink (where multiple users transmit simultaneously to single base station (BS)) and downlink (where the BS transmits to multiple independent users). The uplink challenge is addressed using array processing and multi user detection techniques by the base station in order to separate the signals transmitted by the users. The downlink challenge is somewhat different. MU-MIMO downlink channel is similar to that of SU-MIMO except for the fact that the receiver antennas are distributed among different independent users as shown in Fig. 1(d). This creates a challenge in decoding the received symbols since joint decoding requires each user to have the symbol received from all the receiver antennas of all the users. It is practically impossible to achieve this level of coordination between all the users. Almost all the proposed techniques ideated for addressing the MU-MIMO downlink challenge employ processing of data symbols at the transmitter itself, that is, precoding.

Although precoding is not a new concept and has been used in SU-MIMO systems as well, it was optional and used only to improve SNR at the receiver. However in MU-MIMO systems precoding is essential to eliminate or minimize multi-user interference. Precoding is performed with the help of downlink channel state information (CSI), it requires the transmitter to know the downlink CSI of each user.

Cooperative schemes have been recently proposed as an effective solution to deal with the effects of fading channels and to improve the performance of interference-limited wireless systems [4,5] (Fig. 1(e)). Such cooperative schemes typically include the conventional relaying between user terminals, but may be extended to cooperation between base stations. This last form of cooperation may find one of its main applications in the downlink of multi-cell wireless networks. In this case, the BS transmit the signals to the users within their cell but they can also cooperate in order to implement a joint resource allocation scheme across the cells.

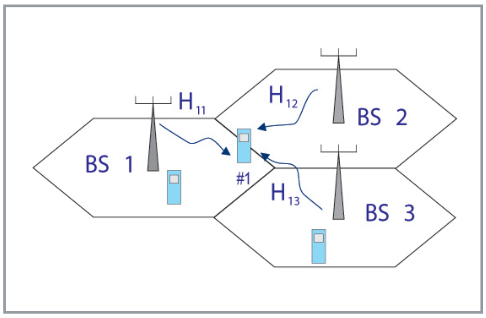


Figure 2. *Example of distributed network coordination for a multi-cell system with three BSs*

Assuming that the BS are connected via a high-speed backbone (Fig. 1(f)), a more advanced form of cooperation based on signal processing techniques is possible. Generally speaking, the antennas from different BS can transmit coordinately and each user can receive useful signals from several BS (Fig. 2). This form of multi-cell processing has been reported in the existing literature as network coordination [6] and can be formulated as a spatially distributed MIMO downlink problem. Several challenges existing in cooperative systems are currently tackled at the iTEAM research Institute. For instance, several sub-optimal algorithms for designing multi-base beamformers with per-base station power constraints were presented in [7]. Moreover, other advantages of the coordinated transmission, including power gain, channel rank improvement and macrodiversity protection were also addressed.

The paper is structured as follows. Section II is focused on spatial multiplexing MIMO systems and presents an state-of-the-art review of existing MIMO detection techniques together with our current research on this topic. Section III deals with cooperative MU-MIMO systems and describes an overview of the application of precoding techniques to MU-MIMO systems with distributed network coordination. Several advances on this topic developed at our research group are also pointed out.

2. Detection in spatial multiplexing MIMO systems

In a spatial multiplexing MIMO system, the data stream is split equally into n_t transmit antennas and simultaneously sent to the channel, thus overlapping time and frequency. The signals are received by n_R receive antennas, as shown in Fig. 3, and the receiver has the task of separating the received signals in order to recover the transmitted data.

The above presented system has usually an equivalent baseband model denoted as

$$x=Hs+v, \tag{1}$$

where s represents the baseband signal vector transmitted during each symbol period formed by elements chosen from the same constellation, such as QAM. Vector x in (1) denotes the received symbol vector and v is a complex white Gaussian noise vector with zero mean and power N_o. For the sake of simplicity, the noise is considered to have unit variance. The Rayleigh fading channel matrix H is formed by n_R x n_t complex-valued elements, h_{ij}, which represent the complex fading gain from the j-th transmit antenna to the i-th receive antenna. Moreover, the channel matrix H is considered known at the receiver.

As said above, MIMO detectors are in charge of separating the transmitted signals with the lowest Bit Error Rate (BER). It is known that Maximum-Likelihood (ML) detection over Gaussian MIMO channels has shown to get the lowest BER for a given scenario. However, it has a prohibitive complexity which grows exponentially with the number of transmit antennas in the MIMO system. Motivated by this, there is a continuous search for computationally efficient optimal or suboptimal detectors, which is a current line of research in our group. In what follows, a state of the art review of MIMO detection algorithms is carried out and some efficient detection schemes developed by ourselves are presented.

2.1. Overview of MIMO Detection algorithms

It can be seen in Fig. 3 that the receive antennas see the superposition of all the transmitted sig-

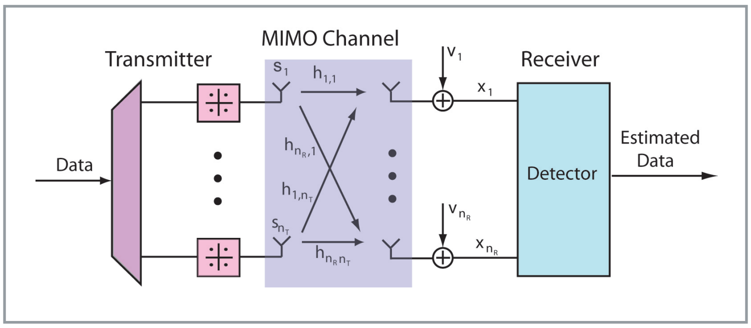


Figure 3. *Spatial multiplexing MIMO system model with n_t transmit antennas and n_R receive antennas.*

nals. Given the received signal x, the detection problem consists in determining the transmitted vector $\hat{s}$ with the highest a posteriori probability. This is typically carried out in practice by solving the following least squares problem

$$\hat{s} = \arg\min_{s \in M^{n_T}} \left\| x - Hs \right\|^2 , \tag{2}$$

where $\hat{s}$ is an n_T-dimensional vector with entries belonging to a M-ary alphabet. Eq. (2) is often called the Maximum Likelihood detection rule.

Fig. 4 shows the classification of nearly most of the existing MIMO detection algorithms. In a first level, detection algorithms can be classified between ML (or exact) methods and almost ML methods. A second classification depends on the way of performing the detection that can be either in a linear way (just multiplying by a matrix in reception) or carrying out a successive interference cancellation (SIC) or via a tree search (Sphere Decoders).

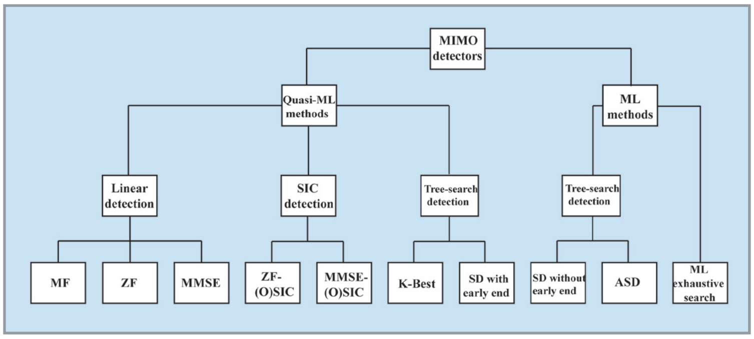


Figure 4. *Classification of MIMO detection algorithms.*

The Maximum Likelihood (ML) detector via exhaustive search is the optimum detector in terms of BER since it gets the exact solution of the ML detection rule (2). Due to the fact that all the possible s vectors belong to a finite n_T -dimensional lattice, the simplest way of finding the solution of (2) is performing an exhaustive search of points in the lattice and selecting the one that minimizes (2). This strategy leads to a very complex algorithm, with a computational cost exponentially growing with the number of transmit antennas. Alternative detectors have been developed in order to decrease this high cost in spite of loosing performance.

The Matched Filter (MF) detector for MIMO appeared as an extension of this detector in SISO channels [8]. The detection step is carried out just by multiplying the received vector by the transpose and conjugate of the channel matrix. Also, a quantization step is needed to round off the result to the closest symbol in the alphabet considered. This algorithm exhibits near optimum behavior when the columns of H are close to be orthogonal.

The Zero Forcing (ZF) detector considers the signal from each transmit antenna as the target signal and the rest of signals as interferers [8]. The main goal of this detector is setting the interferers amplitude to zero and this is performed by inverting the channel response and rounding the result to the closest symbol in the alphabet considered. When the MIMO channel matrix is square ($n_R = n_T$) and non-singular, the inversion step is performed just using the inverse of the channel matrix. However, when the channel matrix is tall ($n_R > n_T$), the pseudo inverse of H is then used. The ZF detector presents the problem of, in some cases, dealing with singular channel matrices that are not invertible.

Another disadvantage is the fact that ZF focuses on cancelling completely the interference at the expense of enhancing the noise. Motivated by this, the MMSE detector appeared. The MMSE detector [8] minimizes the error due to the noise and the interference combined. The performance of already presented algorithms (ZF and MMSE) can be further improved by using nonlinear techniques as symbol cancellation [9]. By using symbol cancellation, an already detected and quantized symbol from each transmit antenna is extracted out from the received signal vector, similarly to what is done in decision feedback equalization or multiuser detection with successive interference cancellation (SIC). Therefore, as soon as a signal is detected, the next one will see one interferer less. However, nulling and cancellation detectors have the drawback of adding interference to the next symbols to be detected, when there has been any wrong decision in the already detected symbols. It can be shown that it is advantageous to find and detect first the symbols with the highest signal to noise ratio, i.e., the most reliable ones. This strategy is known as nulling and cancellation with ordering (O-SIC) [10].

2.2. Sphere Decoding Algorithms

The most recent detection algorithms are the well-known tree search or Sphere Decoding (SD) algorithms. The main interest of SD methods is that instead of performing an exhaustive search over the total n_T-dimensional lattice points, these methods [11] limit the search for the solution to only the lattice points located within a distance of the received vector lower than a given maximum distance, called sphere radius. For instance, Fig. 5 shows the lattice points of a 2x2 MIMO system using a BPSK constellation. It can be seen that if a sphere radius R is chosen, there are only two lattice points that lie inside the sphere, these two points represent the candidate solutions. The ML solution would then be the closest lattice point of the list of candidate points, which is labelled in the figure as ML. These methods can substantially reduce the detection complexity, however, it is necessary to find a suitable value of the sphere radius, what can be difficult in practice.

The search inside the decoding sphere can be performed via a search in a tree, which is built according to the number of transmit antennas

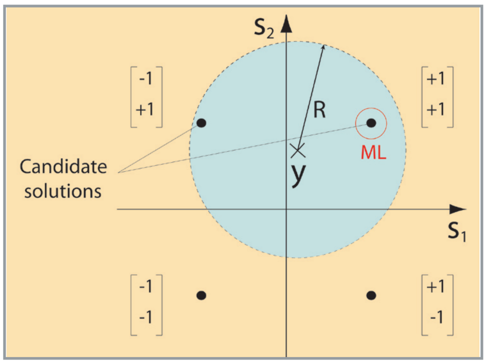


Figure 5. *Decoding sphere of radius R for limiting the candidate lattice points in a 2x2 MIMO system using a BPSK constellation.*

and the size of the constellation employed. In the decoding tree, partial candidate solutions are represented as nodes and branches connecting two nodes have an associated weight that measures the distance to each partial candidate solution to the received vector. The addition of all the branch weights that belong to a tree path, called path weight, is compared to a maximum value (sphere radius), thus discarding the path when this maximum value is exceeded.

Fig. 6 depicts the decoding tree associated to the decoding sphere of Fig. 5, note that the tree will have as many levels as transmit antennas in the system and each node will have as many children nodes as the constellation size. It can be seen that the search for the solution is performed in two levels, in each level branches that lead to a path weight higher than the sphere radius are discarded, resulting in less candidate solutions.

Different tree search strategies have been proposed, some of them can be found in [11], [12] and [13] but they can be classified into two main types of tree search: Depth-First and Breadth-First. In the Depth-First algorithms the tree is explored beginning from the root descending to the leaf nodes, but exploring every child node from left to right. On the other hand, in the Breadth-First algorithms the tree is explored descending level by level up to the leaf nodes, every branch in the same level has to be checked before starting to visit the following level.

K-Best algorithm [12] is a Breadth-First tree search algorithm that stores at each level of the tree only those K paths that show the smallest path weights (K-Best paths). Note that this method is not an actual sphere decoder, since now the candidate solutions are not discarded using a sphere radius but having a list with a fixed number of stored paths up to the current level. The detected signal vector $\hat{s}$ is given by the path from the root up to the leaf node with the smallest path weight. The main advantage of this method is that the maximum number of paths is limited, that yields a fixed computational effort and makes the algorithm hardware implementation easier. Variants of this algorithm also include a sphere radius in order to reduce the number of explored paths [14] but unfortunately, this number is then non-fixed and unknown.

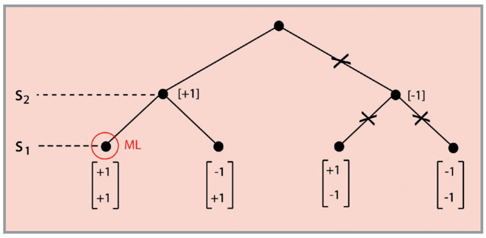


Figure 6. *Decoding tree associated to the decoding sphere of Fig. 5.*

The MIMO channel matrix condition number is strongly related to the performance of suboptimal detection schemes.

Regarding our recent research, it has been mainly focused on improving both the detection performance and the efficiency of K-Best algorithms. Some novel schemes will be presented throughout the following subsection.

2.3. Efficient detection schemes developed at the iTEAM

As it was shown in [15], the channel matrix condition number is strongly related to the performance of suboptimal detection schemes, since it is a measure of how the original constellation is distorted after being transmitted through the channel. It can also be shown that the condition number increases with the size of the channel matrix [16], so for a higher number of antennas, the detection degradation will increase.

Currently, our research is focused on classifying channels according to their condition number, in order to only employ high cost detectors when they are strictly necessary. As an example, in [17] we proposed a combined detector that always works with a K-Best detector but it can select a low value of K while working with well-conditioned channels and switch to a higher value of K when the channel is ill-conditioned. This way, a greater decoding tree is visited when dealing with poor quality channels, thus there is less probability of discarding the ML solution too early.

With the aim of making the proposed detection schemes implementable in practical systems, we are also working towards the design of efficient estimators of the channel matrix condition number. Some condition number estimators together with different methods of choosing the threshold condition number that determines the border between good and bad channels appear in [18].

If the columns of the channel matrix H are considered as the bases of a lattice, Lattice Reduction (LR) strategies can be used to transform the channel matrix H into a new channel matrix $\widetilde{H}=HT$ with more orthogonal columns, where T is an unimodular transformation matrix ($det(T) = \pm I$). Considering the transformation matrix T into the system model (1), the received signal vector x can be rewritten as

$$x = HTT^{-1}z+v = \widetilde{H}z+v, \tag{3}$$

where the symbols to be detected become $z = T^{-1}s$ Note that the transformation T does not affect the observations vector x.

Authors in [19] showed that the performance of K-Best detector can be substantially improved by performing a previous LR of the channel matrix, at the expense of increasing the preprocessing complexity. Following the idea of the above described detector, we are implementing a Lattice-Reduction-Aided (LRA) detector based on condition number that always works with a K-Best detector but it performs a LR of the channel matrix only when the channel is bad-conditioned. As in the already proposed scheme, a previously selected threshold determines good-conditioned and bad-conditioned channels. There exist several LR methods, in our work we are considering the use of either LLL [20] or Seysen's [21] algorithms.

Recently, the iTEAM has purchased a Software-Defined-Radio 2x2 MIMO prototype, depicted in Fig. 7. This prototype is going to be employed to test in a real environment most of the software for MIMO systems implemented in our group, in order to analyse the limitations of the algorithms under real conditions and to help us with the task of improving them as much as possible. The purchased system requires important work before being suitable for performing real testing of MIMO algorithms, thus, making it work properly is one of the current challenges of the research group.

3. Multi-User Coordinated MIMO Systems

As seen in section 1, cancelling or minimizing inter-user interference is necessary in MU-MIMO systems. Dirty Paper Coding (DPC) [22] is a technique that intends to null the interference experienced by one user from the rest of users, just pre-cancelling these last ones at the transmitter. For a given encoding order, if DPC is successively applied to the second, third and following users, only the interferences produced by those who are placed above can be cancelled. In order to cancel the interferences introduced by users placed below, a LQ decomposition of the channel matrix is previously calculated, and an equalization of the Q matrix is carried out in order to obtain a lower triangular channel matrix. This type of precoding, commonly known as Zero Forcing Dirty Paper Coding (ZF-DPC), is shown in Fig. 8 and it has been proved to achieve maximum sum-rate in a multi-antenna multi-user network [23].

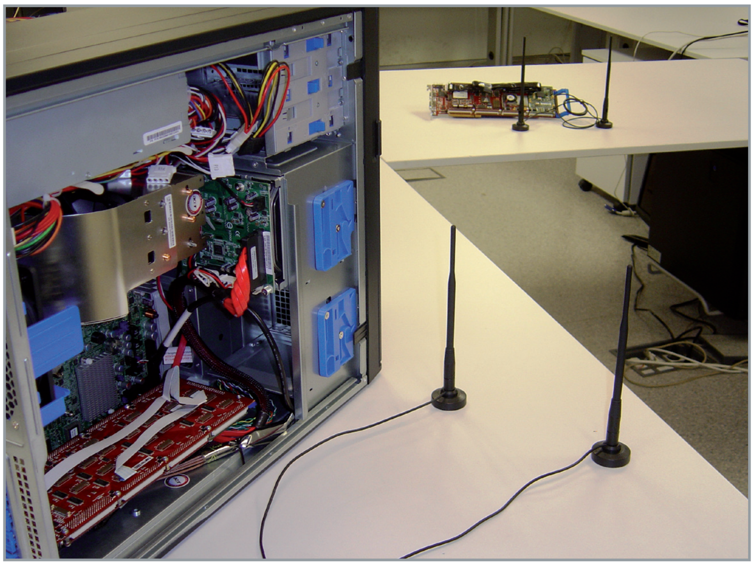


Figure 7. *MIMO 2x2 prototype at the GTAC laboratory of the iTEAM*

Assuming M users, MU-MIMO systems capacity are limited by an M-dimensional region, where each point represents a vector formed by the set of rates simultaneously reached by the M users. The capacity region boundary, called sum-capacity, is an important feature since it represents the set of points where the sum-rate is maximum. The main results of the capacity in MU-MIMO systems, from an information theory point of view, can be found in [24,25].

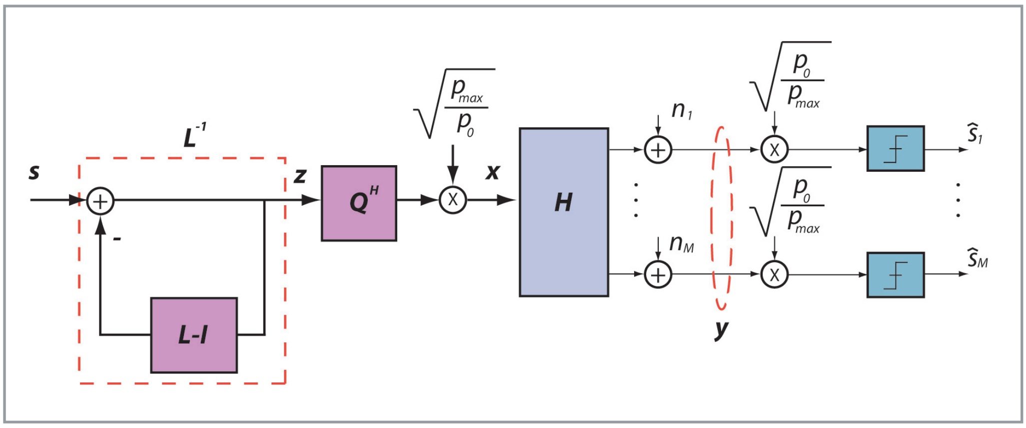
It is well known that if global CSI and complete knowledge of the transmitted signals are available at the transmitter side, DPC is optimum in the sense that achieves the maximum value in the system capacity region [26]. However, in a coordinated network where the BSs are distributed in several cells, global CSI requirement means that heavy traffic load must be supported by the connecting backbone. Moreover, instantaneous estimation of all the BSs fading gains is needed due to the time-variant nature of wireless channels, but instantaneous transmission of them seems extremely inconceivable.

3.1. Dirty Paper Coding in distributed coordinated networks

Nowadays, our research is aimed at coordination techniques which require only local channel information to exploit the benefits of coordinated multi-cell systems. In this case, each user still needs to feed back its channel with respect to each BS, but system complexity is reduced since a quite lower backbone traffic is needed.

Consider a wireless or mobile communication system with N BSs equipped with N_a antennas and M single-antenna users. In our distributed network coordination approach, BSs know their own local channel matrix, ignore the rest of the BSs channels, and only exchange user data and synchronization information with the global network. Then, received signals at the M users transceivers can be expressed by means of vector y as:

$$\mathrm{y} = \sum_{k=1}^{N} \mathrm{H}_k \mathrm{x}_k + \mathrm{n}, \tag{4}$$



■ **Figure 8.** *Illustration of Dirty Paper Coding scheme.*

where y is a vector whose M elements are the received symbols of each users, and H_k is the channel matrix at the k th BS, whose $M \times N_a$ elements, $h_{(i,j)}$, describe the signal fading from the j th BS antenna to the i th user. Vector x includes the precoded information symbols and n is the received noise, which is spatially and temporally white and is also uncorrelated with the signals.

In this scenario, ZF-DPC is locally calculated at each BS for user local channels involved, so users receive different contributions without interference. As in practical systems, the available maximum transmitted power is limited, so a sum-power constraint has to be imposed (P_{max} in Fig. 8). From the point of view of sum-rate maximization, a fair distribution of the available transmit power between all the BSs should be the best choice since the network is not aware of the local channel magnitudes.

Another field of research is the analysis of how much limited feedback is needed in order to reduce the amount of necessary information in the system but keeping good performance in system capacity. In this sense, we are also studying the sum-rate in systems whose users only feed back those channel amplitudes that are higher than a threshold. This case implies a trade-off in the system between cancelling interference and distributing the power efficiently [27].

4. Conclusion

Throughout this paper an overview of MIMO wireless techniques has been presented. The challenges of MIMO systems where our research is mainly concentrated have been highlighted. Especially, the problems of efficient detection in point to point MIMO systems and interference cancellation in coordinated MU-MIMO systems have been discussed. Finally, some of the solutions to these problems that have been carried out at the iTEAM and future research lines have been also pointed out.

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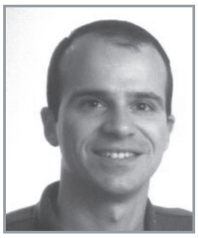

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