In-Network-Processing for Small Cell Cooperation in Dense Networks

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***Abstract*—In dense mobile network deployments, the cooperation of base stations in the uplink promises performance gains w.r.t. area throughput and power efficiency. In this paper, we propose the use of a distributed consensus-based estimation algorithm for the linear equalization of multiple user signals occupying the same resources. We will show that using an iterative process, the same estimation quality can be achieved as if a centralized joint detection of the signals was performed, and that with a limited number of iterations, a satisfactory bit error performance can be achieved.**

I. Introduction

In the recent years, cooperative communication has been identified as a promising way to overcome the throughput bottlenecks and coverage inadequacies of mobile communication systems. In the EU FP7 ICT project iJOIN, a dense, heterogeneous deployment of base stations, termed iJOIN Small Cells (iSCs) is proposed. In such a dense deployment, users often are in the coverage range of several iSCs, since an overlap or overlay of cells, e.g., macro and femto cells is unavoidable and desired. This scenario, e.g., allows for a joint detection and decoding of the UE messages transmitted in the uplink. A straightforward approach is the centralized joint processing of raw baseband receive signals forwarded from the iSCs to a central entity, as designed in cloud RAN (e.g., [1]) deployments, often termed "Distributed Antenna System" (DAS). There also exists a variety of distributed approaches for Cooperative Multi Point (CoMP) processing, as detailed, e.g., in [2], ranging from non-iterative techniques such as interference subtraction [3] to iterative distributed decoding schemes [4]. In this paper, we propose the joint detection of multiple UE signals by means of a decentralized, iterative distributed signal estimation algorithm. In [5], we presented a generic consensus-based In-Network Processing (INP) algorithm for use in arbitrary networks of sensors, which was further investigated in [6] with regard to its behavior in the presence of erroneous inter-sensor communication. The algorithm directly was derived from an optimization problem using strict mathematic theory and shows a faster convergence than other algorithms.

The remainder of this paper is structured as follows: In section II, we will present the scenario investigated and define the system model. The subsequent section III will introduce the consensus algorithm and explain its workings. In section IV, the parameters of numerical simulations and their results are presented in order to give an initial assessment of the performance that can be achieved using the distributed estimation algorithm. The paper is concluded by section V.

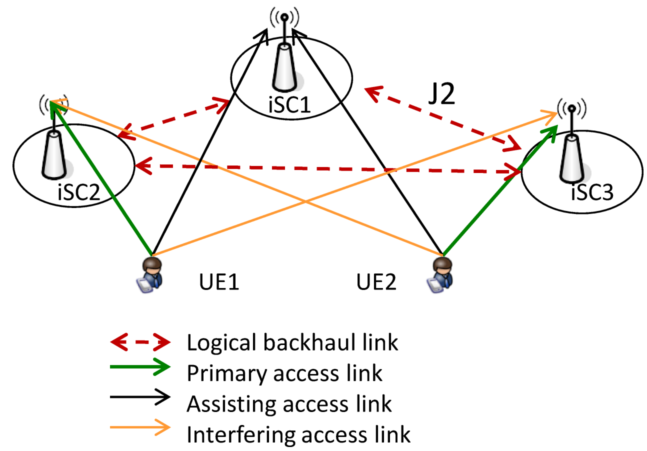

Fig. 1. Illustration of the cooperative uplink scenario

II. Scenario and System Model

In this work, we will apply this algorithm to the problem of linear Multi-User Detection (MUD) in mobile communication systems, as, e.g., an LTE system. Fig. 1 illustrates an example of this scenario: 2 users, UE1 and UE2, operating on the same time and frequency resources, are in reach of 3 iSCs. Since UE1 has the best access link quality on the link to iSC2, this is defined to be the primary access link for UE1. The same is true for the link between UE2 and iSC3. At both these iSCs, the corresponding "non-primary" UE appears as interfering UE. iSC1 does not have any UE allocated on the corresponding time and frequency resources and can assist in the detection process by contributing its received superposition of UE1's and UE2's transmit signals. In the example scenario, every iSC is able to exchange information with every other iSC through a logical interface termed J2, spanning a logical iSC backhaul network. Through iterative information exchange, the iSCs tend to find a consensus on the data symbols transmitted by the UEs. This equalized data could then be forwarded into a cloud based processing entity (named "RAN as a Service", RANaaS), where detection, decoding and all higher layer processing takes place.

The transmitted data symbols of user ℓ on the different spatial layers on a certain resource element, i.e., frequency and time, are collected in a vector $\mathbf{s}^{(\ell)} \in \mathcal{A}^{N\times 1}$ of length N, with $\mathcal{A}$ being an arbitrary real-valued[1] symbol alphabet[2]. At the iSC j, a vector $\mathbf{x}_j \in \mathbb{R}^{M\times 1}$ of length M representing the superposition of the N_U users' different signals, each multiplied with an effective channel matrix $\mathbf{H}_{j,\ell} \in \mathbb{R}^{M\times N}$, comprising also precoding, if any, is received:

$$\mathbf{x}_j = \sum_{\ell=1}^{N_\mathrm{U}} \mathbf{H}_{j,\ell}\mathbf{s}^{(\ell)} + \mathbf{n}_j. \tag{1}$$

$\mathbf{n}_j$ here denotes an additional white gaussian noise (AWGN) term with variance σ_n^2. In our considerations, we assume that the matrices $\mathbf{H}_{j,\ell}$ stem from a Gaussian distribution with zero mean and certain per-link variance $\sigma_{j,\ell}^2$, in order to be able to consider different signal powers and fading on the different links.

In order to give a more compact representation, we introduce the data vector $\mathbf{s} \in \mathcal{A}^{N_\mathrm{U}N\times 1}$ containing the vertically stacked data vectors $\mathbf{s}^{(\ell)}$ of all N_U users and the channel matrix $\mathbf{H}_j \in \mathbb{R}^{M\times N_\mathrm{U}N}$ obtained from a horizontal concatenation of the matrices $\mathbf{H}_{j,\ell}, \ell = 1, \ldots, N_\mathrm{U}$. (1) can then be replaced by

$$\mathbf{x}_j = \mathbf{H}_j\mathbf{s} + \mathbf{n}_j. \tag{2}$$

To perform a joint Zero Forcing (ZF) MUD, the common solution of the J seperate Least Squares (LS) problems

$$\arg\min_{\mathbf{s}'} ||\mathbf{x}_j - \mathbf{H}_j\mathbf{s}'||^2 \tag{3}$$

over all iSCs j has to be found. It can be obtained if the receive vectors $\mathbf{x}_j$ of all J receiving iSCs are stacked to vectors $\mathbf{x} \in \mathbb{R}^{JM\times 1}$ and the matrices $\mathbf{H}_j$ are combined in one large matrix

$$\mathbf{H} = \left\{ \begin{array}{ccc} \mathbf{H}_{1,1} & \ldots & \mathbf{H}_{1,N_\mathrm{U}} \\ \vdots & \ddots & \vdots \\ \mathbf{H}_{J,1} & \ldots & \mathbf{H}_{J,N_\mathrm{U}} \end{array} \right\}.$$

The overall system can then be described by the expression

$$\mathbf{x} = \mathbf{H}\mathbf{s} + \mathbf{n}. \tag{4}$$

The ZF solution, i.e., the solution of the optimization problem

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}'} ||\mathbf{x} - \mathbf{H}\mathbf{s}'||^2 \tag{5}$$

is then obtained by the well-known Moore-Penrose pseudo inverse:

$$\hat{\mathbf{s}} = (\mathbf{H}^\mathrm{H}\mathbf{H})^{-1}\mathbf{H}^\mathrm{H}\mathbf{x}, \tag{6}$$

since $\mathbf{H}$ can be assumed to be a tall matrix, i.e., $JM > N_\mathrm{U}N$. This solution can easily be obtained if all received vectors $\mathbf{x}_j$ and all channel matrices $\mathbf{H}_{j,\ell}$ are available. In a wireless network, these quantities would have to be collected and merged in a central location, often termed "Data Fusion Center" in the context of Wireless Sensor Networks (WSNs). It is obvious that the forwarding of receive data and channel state information consumes resources on the backhaul network, which usually is of heterogeneous nature, and might here and there exhibit bottlenecks, e.g., on backhaul links implemented using wireless technology. Therefore, the distributed processing, consisting of local estimation on the iSCs combined with iterative improvement, leveraged through mutual information exchange, allows for a traffic relief on the backhaul links. The workings of the proposed algorithm are detailed in the following section.

[1]The actual implementation of the estimation algorithm is only working on real-valued variables, but an extension of it is straightforward. Furthermore, using a widely linear representation, every complex valued system can be described by a real valued system of double dimensions.

[2]If the different users employ different modulation alphabets, $\mathcal{A}$ is the union of these. This is unproblematic, since the linear equalizer is unaware of the discrete nature of the alphabet anyway.

III. Algorithm

The distributed linear estimation algorithm originally presented in [5] performs an estimation based on the LS criterion and therefore allows for a ZF or Minimum Mean Square Error (MMSE) equalization of the received signals. It shows the advantage, that at the seperate iSCs, only local channel knowledge (acquired through channel estimation, which is beyond the scope of this paper) is required for calculation of an initial estimate of the combined UE transmit signals. Each estimate is then forwarded to the other iSCs who incorporate it into their estimation process and thus improve their local estimates. Like for comparable algorithms (e.g., [7], [8], [9]), through an iterative process of exchanging intermediate estimates and other auxiliary variables, a consensus on the estimates is achieved, which can be proven to be identical to the centralized LS estimation result a central processing entity would achieve. As detailed in [5], by use of the Augmented Lagrangian method [10] and the Alternating Direction Method of Multipliers [11], [12], the update equations of the iterative algorithm are obtained:

$$\hat{\mathbf{s}}_j(k+1) = \left(\mathbf{H}_j^\mathrm{T}\mathbf{H}_j + \frac{|\mathcal{N}_j|+1}{\mu}\mathbf{I}\right)^{-1} \tag{7}$$
$$\cdot \left[\mathbf{H}_j^\mathrm{T}\mathbf{x}_j + \sum_{i\in\mathcal{N}_j\cup\{j\}} \left(\boldsymbol{\lambda}_{j,i}(k) + \frac{1}{\mu}\mathbf{z}_i(k)\right)\right],$$

$$\mathbf{z}_j(k+1) = \frac{\mu}{|\mathcal{N}_j|+1} \sum_{i\in\mathcal{N}_j\cup\{j\}} \left[-\boldsymbol{\lambda}_{i,j}(k) + \frac{1}{\mu}\hat{\mathbf{s}}_i(k+1)\right], \tag{8}$$

$$\boldsymbol{\lambda}_{i,j}(k+1) = \boldsymbol{\lambda}_{i,j}(k) - \frac{1}{\mu}(\hat{\mathbf{s}}_i(k+1) - \mathbf{z}_j(k+1)). \tag{9}$$

$\hat{\mathbf{s}}_j(k)$ here represents the jth node's estimate of the stacked user data symbol vector $\mathbf{s}$ at iteration k. $\mathbf{z}_j(k)$ has the same dimensions as $\hat{\mathbf{s}}_j(k)$ and serves as an intermediate, auxiliary estimate at node j. The variables $\boldsymbol{\lambda}_{i,j}(k)$ correspond to the Lagrange multipliers used internally for the solution of the optimization problem and are specific to one direction of one link between nodes j and i. It can be seen from eqs. (7)-(9) that for the update of the variables at node j, other variables from the set of neighboring nodes $\mathcal{N}_j$ are required. The neighborhood $\mathcal{N}_j$ of node j is defined by the logical topology of the network connecting the receiving nodes. For example, the nodes might be connected by a ring, which means that every node has two neighbors. It is furthermore also possible, e.g., to connect the nodes using a line structure, i.e., the nodes at the end only have one neighbor, while those in between have two neighbors. Please note that we are referring to topology in a logical sense. The physical topology of the backhaul might differ from the logical one and usually is fixed. With regard to logical topology, there often is a degree of freedom which can be exploited in order to accommodate

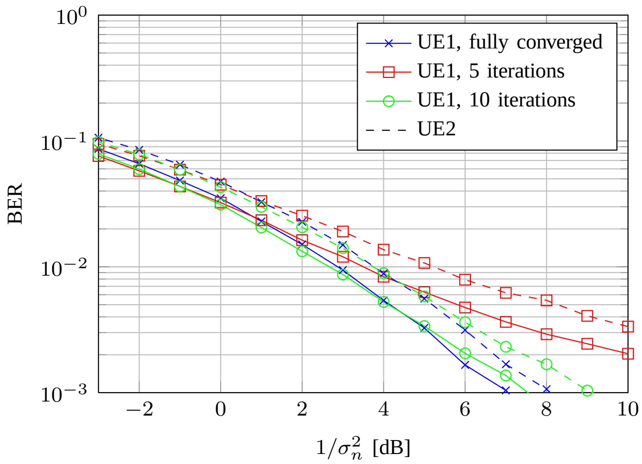

Fig. 2. Simulated bit error rates for a system in ring topology with 2 UEs transmitting 2 spatial layers each, and 3 receiving iSCs with 4 antennas each using the distributed estimation algorithm for a fixed number of iterations (5 and 10) and iteration until convergence is achieved

the properties of the physical link. E.g., if the backhaul is constrained w.r.t. throughput, it should be avoided to set up too many logical links between the iSCs. The effect of different logical topologies will be investigated in the following section.

IV. Simulation Results

In order to assess the achievable bit error performance and its dependency on the number of iterations, Matlab simulations have been performed for a distributed ZF equalization. For these simulations, the N_{U} UEs were assumed to transmit unit power BPSK symbols on each of their N spatial layers. For each link between UE ℓ and iSC j, a channel matrix with real valued, i.i.d., coefficients from a zero mean normal distribution with variance $\sigma^2_{j,\ell}$ was assumed. At each of the N_R receive antennas at each of the J iSCs, a real valued, zero mean, i.i.d, Gaussian noise of variance σ_n^2 was added to the superposition of the UEs' signals. The stepsize parameter μ was chosen to 1.

The uncoded bit error rate has been determined based on the linear equalizer output after a fixed number of 5 and 10 iterations, and after sufficiently many iterations to ensure that convergence has been achieved[3]. Fig. 2 shows the bit error curves for $N_{\mathrm{U}} = 2$, $J = 3$, $N = 2$ and $M = 4$, which means that every iSC is by itself generally capable to separate the two users spatially. The individual channel gains per link had been chosen to $[\sigma^2_{j,\ell}] = \begin{bmatrix} 0.1 & 1 & 0.5 \\ 0.15 & 0.2 & 1 \end{bmatrix}$. As can be seen for the ring topology in Fig. 3, the average number of iterations required until convergence was observed to be 16-18, increasing with the noise power, with a standard deviation of 5-7, also increasing with the noise power. Nevertheless, it can be seen that with a fixed number of 10 iterations, the encountered SNR loss is less than 1 dB. With only 5 iterations, however, the BER performance degrades significantly. It shall also be noted that in the low SNR regime, the bit error rate for the fully converged case is slightly larger than for the cases of 5 or 10 iterations. This can be explained through investigation of (7): In the first iteration, the initial estimate of the joint user vector $\mathbf{s}_j(1)$ at node j is given by

$$\hat{\mathbf{s}}_j(1) = \left(\mathbf{H}_j^{\mathrm{T}}\mathbf{H}_j + \frac{|\mathcal{N}_j|+1}{\mu}\mathbf{I}\right)^{-1}\mathbf{H}_j^{\mathrm{T}}\mathbf{x}_j. \qquad (10)$$

This expression can be interpreted as a modified solution of (2), a non-cooperative ZF MUD with the pseudo inverse regularized by $\frac{|\mathcal{N}_j|+1}{\mu}$. It is known that the MMSE solution basically also contains a regularized pseudo inverse and outperforms the ZF solution in the low SNR regime. Obviously, our system is dominated by noise and not by interference in the region below approx. 4 dB. Therefore, the use of the MMSE criterion for the optimization problem (5) promises a better performance in the low SNR regime. It is subject of ongoing work.

If the number of spatial layers per UE is increased to $N_{\mathrm{U}} = 4$, a single iSC is not able to spatially seperate the users any longer, since (2) is underdetermined. Therefore, the initial estimate of the iSCs before any neighboring iSC's information is incorporated is very poor. Thus, the number of required iterations is increased drastically, to average values of 27-47, depending on the noise power. The corresponding standard deviation lies between 9 and 30. Not surprisingly, thus, at 5 and 10 iterations, the estimated signal still contains a significant amount of interference, leading to an error floor visible in Fig. 4.

The simulations have been repeated for a line topology with iSC2 being placed in the middle and iSCs 1 and 3 at the ends of the line. The resulting bit error curves can be seen in Figs. 5-6. It can be observed that the bit error performance for the converged case is the same, as it is expected, since it corresponds to the central solution (6). For the cases with a fixed number of iterations, the bit error performance is slightly improved. Investigating the average number of required iterations and its standard deviation as depicted in Fig. 7, one can see that it is slightly smaller than in the case of the ring topology. This observation is contrary to the general expectation that more links in a network with a certain number of nodes will lead to a faster convergence. In the investigated scenario, the use of 2 logical links between the nodes obviously is sufficient. Interestingly, there is no relevant

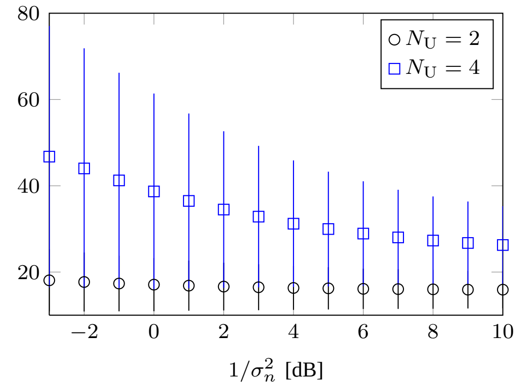

Fig. 3. Average number of required iterations ± standard deviation for convergence in the case of a ring topology

[3] As stopping criterion, the sum over all nodes of the norms of the gradients of the seperate cost functions had been compared to a threshold. The authors are well aware that this centralized stopping criterion cannot be implemented in a distributed system, but it shall only serve as a reference for these simulations.

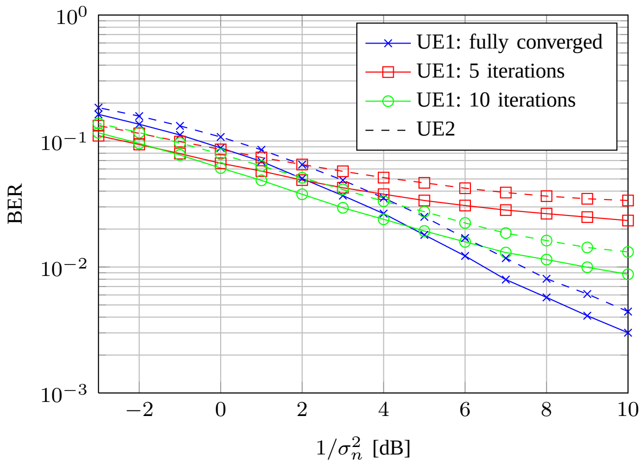

Fig. 4. Simulated bit error rates for a system in ring topology with 2 UEs transmitting 4 spatial layers each, and 3 receiving iSCs with 4 antennas each using the distributed estimation algorithm for a fixed number of iterations (5 and 10) and iteration until convergence is achieved

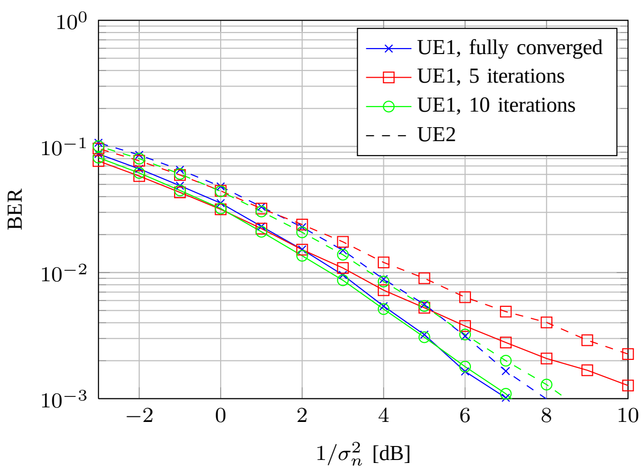

Fig. 5. Simulated bit error rates for a system in line topology with 2 UEs transmitting 2 spatial layers each, and 3 receiving iSCs with 4 antennas each using the distributed estimation algorithm for a fixed number of iterations (5 and 10) and iteration until convergence is achieved

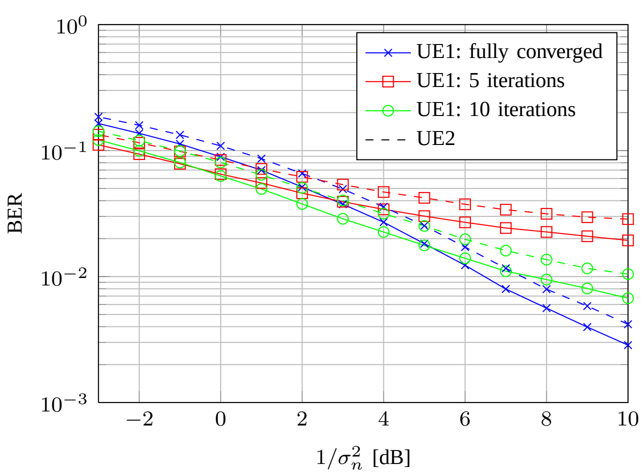

Fig. 6. Simulated bit error rates for a system in line topology with 2 UEs transmitting 4 spatial layers each, and 3 receiving iSCs with 4 antennas each using the distributed estimation algorithm for a fixed number of iterations (5 and 10) and iteration until convergence is achieved

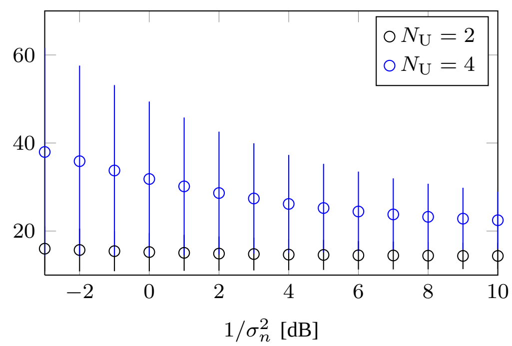

Fig. 7. Average number of required iterations $\pm$ standard deviation for convergence in the case of a line topology

difference in the average number of iterations if two other links are set up, e.g., with iSC1 being in the center and iSC2 and iSC3 at the ends. The mean value increases by only a fraction of an iteration.

However, if the number of nodes is increased, a higher connectivity will lead to a faster convergence. For instance, previous own investigations [13] have shown that for e.g. 6 nodes, a ring topology requires less iterations with smaller standard deviation than for the line topology. A full mesh, however, leads to an even further reduced number of iterations.

V. Conclusion and Future Work

In this paper, we proposed the use of a consensus-based estimation algorithm for the joint equalization of multi-user signals in a cellular network environment. We reviewed the algorithm and detailed on the information that needs to be exchanged for the iterative updating. The bit error performance was evaluated using numerical simulations for a given scenario with varying parameters, in particular number of spatial layers per user and network topology. We showed that even with a limited number of iterations, an acceptable performance can be achieved.

The results shown in this paper are supposed to be an initial assessment of the performance gains achievable through base station cooperation and therefore only use a simple model. A more realistic scenario will comprise significantly more users and iSCs and will also incorporate heterogeneous, non-ideal backhaul.

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