Iterative Soft-In Soft-Out Sphere Detection for 3GPP LTE

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***Abstract*—3GPP LTE has become a hot topic in recent years. One of its main challenges is the computationally intense task of MIMO detection. This paper investigates MIMO detection methods based on Sphere detection for 3GPP LTE system. A 3GPP LTE simulation chain has been developed for the evaluation. The results show that TS algorithm in combination with complexity reduction techniques of SSD and ME achieves a good tradeoff between performance and complexity for three different user scenarios. Furthermore, the results show the performance improvement achieved with SISO detection at low complexity. To the best of our knowledge, this is the first reported work about SISO detection for 3GPP LTE.**

I. Introduction

3GPP Long Term Evolution (LTE) is the fourth generation mobile wireless broadband technology. Its key objective is to enhanced spectral efficiency by using multiple-input multiple-output (MIMO) techniques. However, this performance improvement comes at the cost of increased computational complexity in the receiver. One of the main challenge is the computationally intense task of MIMO detection use to separate the spatially multiplexed data streams.

MIMO detectors with reasonable complexity, like linear detectors (ZF or MMSE) [1] and nonlinear detectors like Successive Interference Cancellation (SIC) [2], do not provide a detection accuracy close to maximum likelihood (ML) detection, limiting their field of application. Therefore, many recent research try to solve this problem by introducing complexity reduced detection algorithms based on tree search techniques. Application of depth-first, breadth-first or metric-first search strategies [3] leads to a large variety of detection algorithms like the sphere detector [4], list sphere decoder [5], m-algorithm [6], LISS-algorithm [7] or modifications of them [8]–[10]. The Tuple Search (TS) algorithm [11] together with the application of Search Sequence Determination (SSD) [12] and Metric Estimation (ME) [13] provides detection performance close to maxLogAPP at low detection complexity. However, none of the above mentioned MIMO detectors has been evaluated for 3GPP LTE system. The work published in [14] provides some results for 3GPP LTE setup but they are only for hard output detection. The introduced algorithm is not applicable for soft in soft out (SISO) detection, which could be applied to further improve the detection performance. Furthermore, results are provided only for suburban 3GPP LTE scenario.

The focus of the work presented in this paper is to evaluate the performance and complexity of MIMO detection for 3GPP LTE system. This work is based on the algorithm proposed in [11] together with the complexity reduction techniques of SSD and ME presented in [12] and [13] respectively. We have shown how the complexity of the detection is reduced without significant performance loss by using TS-SSD-ME algorithm (TS algorithm together with SSD and ME) for three different user scenarios specified in 3GPP LTE Release 8. This algorithm also enables high performance SISO detection at low complexity and allows flexible adaptation of the complexity and the achievable performance over the tuple size of a given detector. It is applicable independent of the size of QAM constellation. Complexity of its potential hardware implementation is reduced due to reduction of information to be stored, less operations needed for the list maintenance and simplified L-value calculation.

The remainder of this paper is organized as follows: Section II introduces the system model; Section III reviews tree search based SISO detection. Section IV presents the TS algorithm. Section V is about SSD and ME. Finally we evaluate the TS-SSD-ME algorithm in section VI and conclude the paper in section VII.

II. System model

In this paper, we consider 3GPP LTE system with N_{T} transmit and N_{R} receive antennas as depicted in Figure 1. A vector $\mathbf{u}$ of independent and identically distributed (i.i.d.) information bits is encoded by the outer channel code with rate R. The resulting code bit stream $\mathbf{c}'$ is bit-interleaved and portioned into N_{T} blocks $\mathbf{c}$ of $n \cdot N \cdot L$ bits. Here n is the number of OFDM symbols per frame, N is the number of subcarriers per OFDM symbol and L denotes the number of bits per symbol. For the transmission, the corresponding bits in every single block $\mathbf{c}$ are mapped (e.g. gray mapping) onto a complex constellation symbols $\mathbf{x} = [x_1, x_2 ... x_{N_{\mathrm{T}}}]^T = map(\mathbf{c})$, whose components are taken from some complex constellation $\mathcal{C}$ (e.g. 64-quadrature amplitude modulation (QAM)). Afterwards the vector is transformed into time domain by performing an inverse fast Fourier transform (IFFT) in OFDM modulator and cyclic prefix (CP) is added to it . We normalize the transmit energy such that $\mathcal{E}\{\mathbf{x}\mathbf{x}^{\mathrm{H}}\} = E_{\mathrm{S}}/N_{\mathrm{T}}\mathbf{I}$. On behalf of the transmission, we consider a flat fading channel and an additive noise vector $\mathbf{n} \in \mathbb{C}^{\mathbf{N}_{\mathrm{R}} \times \mathbf{1}}$ at the receiver with complex components of zero mean i.i.d. gaussian random variables of variance $N_0/2$ per real dimension ($\mathcal{E}\{\mathbf{n}\mathbf{n}^{\mathrm{H}}\} = N_0\mathbf{I}$). The considered passive channel is represented by $\mathbf{H} \in \mathbb{C}^{N_{\mathrm{T}} \times N_{\mathrm{R}}}$ with entries of a zero mean i.i.d. gaussian random process of variance 1 and is assumed to be perfectly known at the receiver. At the receiver the received signal is transformed in to frequency domain by fast fourier transform (FFT) in OFDM demodulator and CP is removed. The resultant signal $\mathbf{y}$ of one OFDM stream is given by:

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

and the signal-to-noise-ratio ($SNR = E_s/N_0$) at the receiver applied to the energy of one information bit can be stated as: $E_{\mathrm{b}}/N_0 = E_s N_{\mathrm{R}}/N_0 N_{\mathrm{T}} LR$. The detection of the transmitted bits is carried out by a complex-valued SISO sphere detector in conjunction with a BCJR based decoder with 8 internal iterations. The detection and decoding might be performed iteratively.

III. MIMO Detection based on Tree Search

A. Fundamentals

The task of the focused detector is the determination of the bits c most likely sent and the calculation of reliability information for these

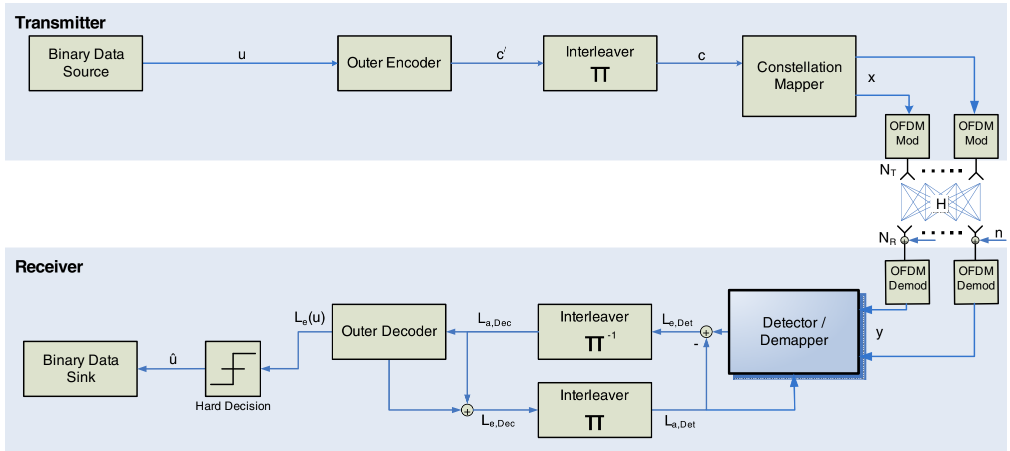


Fig. 1. System model with BICM transmitter and iterative receiver.

bits. On behalf of the described system, this can be accomplished by calculating the corresponding log-likelihood ratios (L-values):

$$L\left(c_{m,l}|\mathbf{y}\right)=\ln\left(\frac{P\left(c_{m,l}=+1|\mathbf{y}\right)}{P\left(c_{m,l}=-1|\mathbf{y}\right)}\right)$$
$$\approx-\frac{1}{N_0}\min_{\mathbf{c}|c_{m,l}=+1}\{\lambda_0\}+\frac{1}{N_0}\min_{\mathbf{c}|c_{m,l}=-1}\{\lambda_0\},\quad(1)$$

where (1) results from the application of the max-log approximation. $c_{m,l}=\pm1$ represents the l-th bit of the symbol sent by the m-th antenna and

$$\lambda_0\left(\mathbf{y},\mathbf{c},\mathbf{L_a}\right)=\|\mathbf{y}-\mathbf{Hx}(\mathbf{c})\|^2-\frac{N_0}{2}\sum_{i=0}^{N_T-1}\sum_{j=1}^{L}c_{i,j}L_a(c_{i,j})$$

represents the distance metric for a set of received symbols $\mathbf{y}$, a given $\mathbf{c}$ and the a-priori knowledge $\mathbf{L_a}$. $\mathbf{x}$ corresponds to a possible transmission symbol. As consequence, beside the most likely sent symbol $\arg\min\limits_{\mathbf{x}(\mathbf{c})|\mathbf{c}\in\mathcal{C}}\{\lambda_0\}$ - the detection hypothesis - and its corresponding metric $\lambda_0(\mathbf{c}^{\mathrm{ML}})$, the detector has to determine also the counter-hypotheses $\arg\min\limits_{\mathbf{x}(\mathbf{c})|\mathbf{c}\in\mathcal{C},c_{m,l}\neq c_{m,l}^{\mathrm{ML}}}\{\lambda_0\}$ with their metrics for each bit.

B. Tree Search Basics

Since brute force (maxlogAPP) detection of (1) is known to be of exponential growing complexity with the number of transmit antennas, several close to optimal detection strategies have been lately proposed to find relevant $\arg\min\{\lambda_0\}$. Some of the most promising are based on tree search techniques. As depicted in detail in [5], transforming the detection problem is permitted by QR-decomposition (QRD) of $\mathbf{H}=\mathbf{QR}$, where $\mathbf{Q}$ is unitary and $\mathbf{R}$ an upper triangular matrix. With the modified received symbols $\mathbf{y}'=\mathbf{Q}^{\mathrm{H}}\mathbf{y}$ and the potential sent symbols $x_i, i=0...(N_T-1)$, the Euclidian distance in the detection

$$\left\|\mathbf{y}'-\mathbf{Rx}(\mathbf{c})\right\|^2\quad(2)$$

can be interpreted as tree search. The search tree and the relevant notations are drafted in Fig. 2 for a 2 QAM and $N_T=4$ transmit antennas. The root node of the tree is defined as layer $i=N_T$. In each of the layers i, $i=(N_T-1)...0$, 2^L possible transmission symbols x_i are existing for one parent node, represented by the nodes of the tree and connected to the parent via branches. Layer $i=N_T-1$, corresponding to the lowest row of (2) and a path from $i=N_T-1$ to $i=0$ represents a complete set of sent symbols $\mathbf{x}$, mapped to the leaves of the tree. Resulting from this, λ_0 can be recursively calculated by the layered branch metric

$$\lambda_i=\underbrace{\lambda_{i+1}}_{\substack{\text{metric from}\\\text{already}\\\text{estimated}\\\text{symbols}}}+\left|\underbrace{y_i''}_{\substack{\text{interference}\\\text{reduced}\\\text{symbol}}}-r_{ii}x_i\right|^2\underbrace{-\frac{N_0}{2}\sum_{j=1}^{L}c_{i,j}L_a(c_{i,j})}_{\substack{\text{a-priori}\\\text{information}}},\quad(3)$$

$$y_i''=y_i'-\sum_{j=i+1}^{N_T-1}r_{ij}x_j,$$

out of the squared distance between the nodes and an interference reduced symbol, the a-priori information and the metric of the corresponding parent node, whereas the root metric is defined to $\lambda_{N_T}=0$. In order to ensure a monotonously growing metric, the a-priori is extended as described in [15].

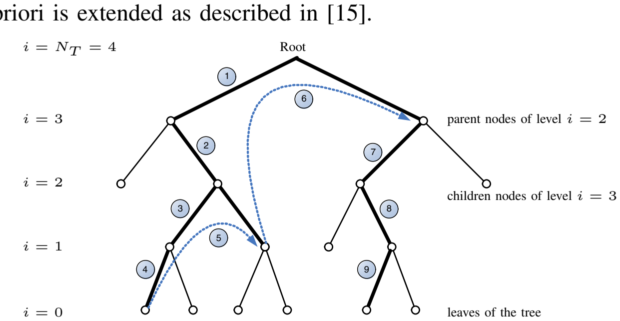


Fig. 2. Example sphere based tree search

Assuming an implementation with one extended node per cycle, as described in [16], the decisive factor for the throughput is the number of extended nodes. The resulting hardware complexity heavily depends on the actual implementation, the included complexity reduction techniques and optimizations. Throughout this paper, hence the number of extended nodes is chosen as complexity measurement.

IV. Tuple Search Algorithm

Computing the L-values in (1) requires determination of a detection hypothesis and all counter-hypotheses as depicted in III-A. Since explicit search for all needed minimums leads to insufficient high complexity [17], the key to efficient detection is the adequate usage of information gathered during the search in combination with an adapted search strategy. One possibility is the application of search tuples and internal clipping to the List Sphere Detector (LSD) [5] as described in detail in [11] and briefly depicted as follows.

TS algorithm proposes the usage of a search tuple for the sphere determination. Instead of searching all possible minima, the TS algorithm searches the T most likely leaves. As the measurement of the nodes' reliability is given by their distance metrics (3), only nodes with a metric smaller than the T best leaf metrics have to be examined. For this, the metrics λ_0 of the T most reliable determined leaves are stored in a search tuple $\mathcal{T} := \{\lambda_0(\mathbf{c}_1), \lambda_0(\mathbf{c}_2), \ldots, \lambda_0(\mathbf{c}_T)\}$. The sphere radius is defined to the maximum tuple metric:

$$R = \max_{\mathbf{c}_t | \mathbf{c}_t \in \mathcal{T}} \{\lambda_{0,t}\}.$$

For initialization, the tuple elements are set to $\lambda_{0,t} = \infty$. Resulting from its definition, the sphere search finds all leaves within the current sphere. Each leaf within the current sphere, identified by the search, hence represents a new element of the tuple, which replaces the worst element of the tuple:

$$\lambda_0(\mathbf{c}) \mapsto \max_{\mathbf{c}_t | \mathbf{c}_t \in \mathcal{T}} \{\lambda_{0,t}\}.$$

Status information for the L-value calculation has to be stored separately in a bit specific storage. The reason being the difference between biased and unbiased metrics caused by MMSE preprocessing and the problem of dropping useful candidates due to limited list size of the LSD. In case of the proposed bias reduced MMSE detection, the lowest $f(\mathbf{c}) \hat{=} f(\lambda_0(\mathbf{c}), \sigma^2, \mathbf{c}) = \lambda_0 - \sigma^2 \|\mathbf{x}\|^2$ have to be stored for the hypothesis and for the corresponding counter hypotheses bits, as illustrated in Figure 3.

Whenever a leaf is reached, the current $\mathbf{c}$, $f(\mathbf{c})$ are compared with the stored values $\mathbf{c}^{\mathrm{ML}}$, $f(\mathbf{c}^{\mathrm{ML}})$

$$\mathbf{c}^{\mathrm{ML}} \leftarrow \arg\min \{f(\mathbf{c}), f(\mathbf{c}^{\mathrm{ML}})\},$$
$$f(\mathbf{c}^{\mathrm{ML}}) \leftarrow \min \{f(\mathbf{c}), f(\mathbf{c}^{\mathrm{ML}})\},$$

and subsequent to this with the corresponding $f(c_i)$

$$f(c_i) \leftarrow \min \{f(\mathbf{c}), f(c_i)\}, \ \forall \ c_i \in \mathbf{c} | c_i \neq c_i^{\mathrm{ML}},$$

whereas the lowest values are stored.

Since the L-value calculation is accomplished over leaves examined during the tree search, probably not all relevant counter-hypotheses were found. Consequently, extrinsic L-values have to be clipped: $|L_e| \leq L_{\max}$ and defining a convenient clipping level $L_{\max}$ is crucial for good performance [8]. Hence, for our simulations the clipping level is chosen such that the average mutual information at the detector output is maximized [18] and transferred to an inner clipping value as proposed in [15].

V. Search Sequence determination and Metric Estimation

TS algorithm uses Schnorr Euchner (SE) enumeration for the selection and analysis of favorable nodes in order to find leaves for (1) early. However, the essential SE enumeration requires calculation of all Q possible child nodes and the selection of the most favorable one. To avoid repeated metric calculations, these nodes are sorted and stored for the selection of subsequent favorable nodes, requiring a complex sorting operation of Q nodes per parent and the storage of $N_t \times Q$ elements. Obviously, this leads to disadvantageous high hardware complexity and detection delay. To solve this problem

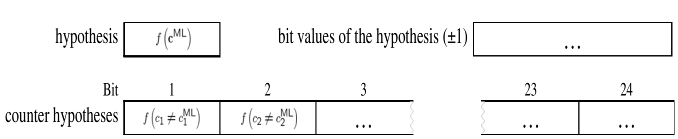


Fig. 3. Bit-specific storage for a 64 QAM and $N_{\mathrm{T}} = 4$

[12] describes a geometrical approach to determine the sequence of favorable child nodes for TS algorithm. Another important factor which increases the complexity of node extension is the required metric calculation. For reduction of this complexity [13] gives an approach based on Metric Estimation. In the following we will briefly discuss these approaches to illustrate their benefits for 3GPP LTE systems.

A. Sequence determination based on relative positions

Without a priori information the reliability of children nodes in (3) is only given by the squared Euclidian distance between the interference reduced symbol y_i'' and the nodes represented by the constellation points $r_{ii}x_i$. By normalizing[1] this relation with $\frac{1}{r_{ii}}$, the reliability is only dependant on the squared distances between a representative of the received symbol y_i''' to a fixed grid of possible sent symbols x_i with given lattice spacing a:

$$\left|y_i''' - \hat{x}_i\right|^2, \text{ with } y''' = \frac{y''}{r_{ii}},$$

With growing distance $|y_i''' - x_i|$ the resulting metric $\lambda_i(x_i)$ enhances and nodes become increasingly unfavorable. Based on this consideration the sequence of favorable nodes can be determined for a given position of y_i'''.

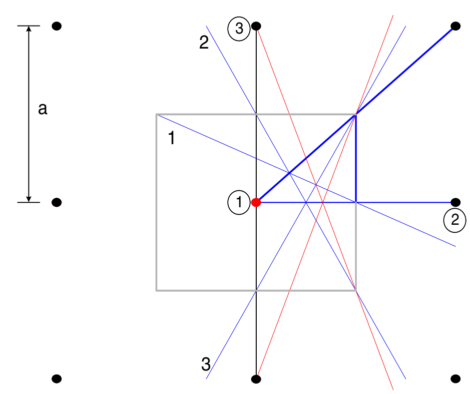


Fig. 4. Search Sequence Determination octet

Independent of the absolute position within the grid, the most favorable node is the node closest to y_i''', easy to determine by rounding y_i''' to the grid points as displayed in Fig.4. This node is taken as a reference node x^r and $\Delta^r = y_i''' - x^r$ gives the relative position. Presuming a Δ^r in quadrant 1 relative to x^r, the nodes marked with ② and ③ in Fig. 4 are potential 2nd favorable nodes. Consequently, for all Δ^r above the angle bisector of quadrant 1 node ③ is the second favorable one and ② the 3rd favorable one and vice versa. For a possibly mapped Δ^r within the spanned triangle[2], two possible subsequent 4th nodes are existing (lower left and upper right node in Fig. 4). Similarly to the determination of the 2nd and 3rd node, a bisector line spanned by the nodes can be used for the determination of the following node, indicated by line 1 in Fig.4. While the 5th element (el.) for the upper right triangle is fixed by default, another case differentiation is needed for the lower triangle, resulting in a comparison with line 2 (Fig. 4). Similarly the determination of the 6th and 7th favorable nodes can be carried out with line 3 (Fig.4). Continuative determination of the sequences results in more complex operations, making their application unattractive as shown in Fig.4 for the determination of the

[1] r_{ii} only contains positive real-values for a convenient chosen QRD.

[2] Spanned by the angle bisector, the real-axis and the vertical line resulting from the rounding operation.

8th node of the sequence. Therefore, [12] uses predefined sequences for further node enumeration without additional case differentiations. These predefined sequences are determined using triangle's centers as reference points.

B. Metric Estimation

The complexity of a loop within the SSD-TS detection is mainly given by the complexity of the contained metric calculation. In order to further increase the efficiency (i.e. relation of detection performance and throughput to the area and power consumption), [13] describes how this complexity can be significantly reduced by metric estimation. As illustrated in previous section for the search sequence determination, the metric calculation can be mapped onto geometrical considerations. Derived from these considerations, the Euclidian distance is given for real valued r_{ii} (provided by a suitable QRD) by

$$\begin{aligned}\left|y_i' - \sum_{j=i+1}^{N_\mathrm{T}-1} r_{ij}x_j - r_{ii}x_i\right|^2 &= r_{ii}^2\left|\frac{y_i'}{r_{ii}} - \sum_{j=i+1}^{N_\mathrm{T}-1}\frac{r_{ij}}{r_{ii}}x_j - x_i\right|^2 \\ &= r_{ii}^2\left|y_i''' - x_i\right|^2, \qquad (4)\end{aligned}$$

whereas the normalization with r_{ii} might be precalculated. Once the relative position of y''' to a reference point within a fixed grid of potential nodes x_i is known, e.g. by calculating Δ^r to the closest node, the relative distances to all nodes are predefined. In the style of the sequence estimation it is consequently possible to estimate the position of y''' and replace the calculation of the Euclidian distances (4) by distances d defined for the determined region:

$$r_{ii}^2\left|y_i''' - \hat{x}_i\right|^2 \mapsto r_{ii}^2 d^2. \qquad (5)$$

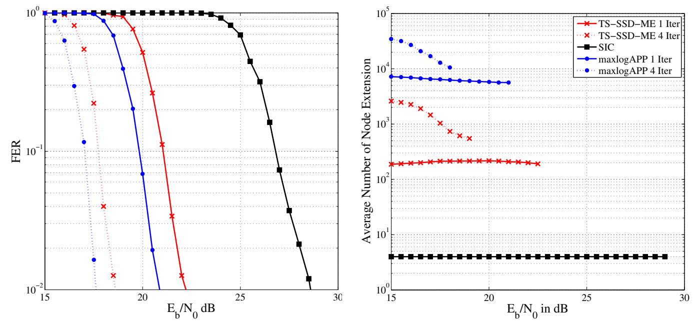
For the remaining computations in (5) it is possible to precalculate r_{ii}^2 as well as $r_{ii}^2 d^2$. The latter however should be only applied selectively for implementation, to avoid increasing amount of precalculations and intermediate data.

Application of SSD and ME to TS algorithm enables the "one node per cycle architecture" of [16] with the amount of metric calculation reduced from Q or 10 [16] to only 3 requiring no sorting anymore. Furthermore, the metric calculation itself is simplified leading to a cycle latency reduced approximately to $\frac{1}{4}$ as compared to state of the art [16]. Consequently power and area consumption are reduced and throughput is increased. This is very useful for future mobile systems specifically 3GPP LTE.

VI. Simulation and Results

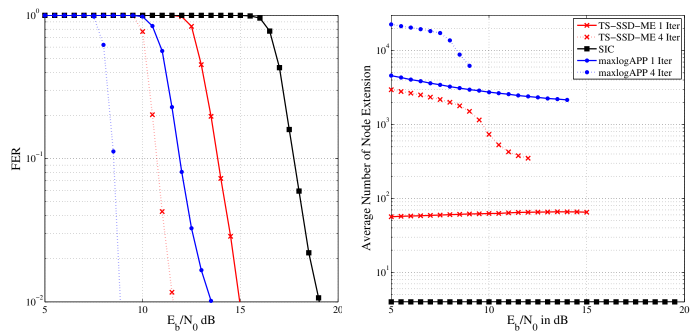
A. Setup

We setup the system according to 3GPP LTE. All simulation are carried out for OFDMA symbol size equal to 512 subcarriers with 300 used subcarriers and cyclic prefix of length 36. Although the detector is suitable for all transmission schemes (4, 16 or 64QAM and upto 4×4 MIMO) without any implementation changes, we have chosen the maximum challenging setup i.e. 4×4 MIMO with 64QAM to illustrate the capabilities of the detector. The Bandwith used is 5MHz. Channel coding is $(11, 13)$ parallel concatenated convolutional code (PCCC) of rate $1/3$. For simulation we apply coded transmissions over three channel models with low, medium and large delay spread as specified in Release 8 for LTE. As described in [19], the low delay spread gives an Extended Pedestrian A (EPA) model which is employed in an urban environment with fairly small cell sizes, while the medium and large delay spreads give an Extended Vehicular A (EVA) model and Extended Typical Urban (ETU) model respectively. These channel models with a carrier frequency of 2.1 GHz and Doppler shifts of 5 Hz, 70 Hz and 300Hz correspond roughly to mobile velocities of 2.7, 36 and 154 Km/h respectively. Table I gives an overview of the main parameters as specified in [19] for EPA, EVA and ETU.



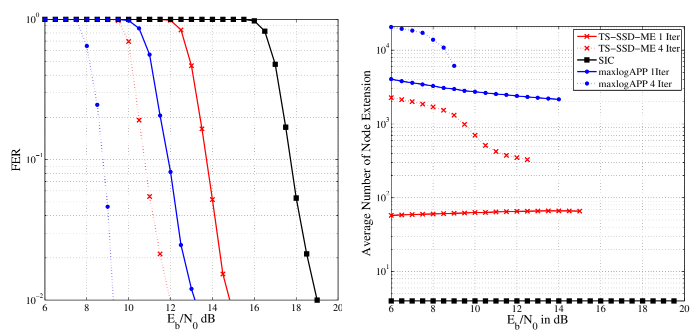
(a) Influence on the FER performance (b) Influence on complexity

Fig. 5. Comparison of the maxlogAPP and the TS-SSD-ME algorithms for LTE system with Extended Pedestrian A channel Model



(a) Influence on the FER performance (b) Influence on complexity

Fig. 6. Comparison of the maxlogAPP and the TS-SSD-ME algorithms for LTE system with Extended Vehicular A channel Model



(a) Influence on the FER performance (b) Influence on complexity

Fig. 7. Comparison of the maxlogAPP and the TS-SSD-ME algorithms for LTE system with Extended Typical Urban A channel Model

B. FER and Complexity

Figure 5 shows the performance and complexity (amount of extended nodes) of various MIMO detection algorithms for Extended Pedestrian A channel model. The FER of the SIC and maxlogAPP respectively sets limits on the minimum and maximum achievable detection performance. While the maxlogAPP (Unclipped Single Tree

TABLE I
EXTENDED ITU CHANNEL MODELS [19]

No	Channel Model	r.m.s. Delay Spread(ns)	Category	Doppler Shift (Hz)	Mobile Velocity (km/h)
1	Extended Pedestrian A (EPA)	43	Low Delay Spread	5	2.7
2	Extended Vehicular A (EVA)	357	Medium Delay Spread	70	36
3	Extended Typical Urban A (ETU)	991	High Dealy Spread	300	154

Search algorithm [9]) gives the best detection performance achieving FER of 10^{-2} at $E_{\rm b}/N_0 = 21$ dB, its complexity is unusable high. The average number of node extensions is 5631 at $E_{\rm b}/N_0 = 21$ dB. SIC on the other hand gives the worst performance and achieves the FER of 10^{-2} at $E_{\rm b}/N_0 = 28.5$ dB but at much reduced complexity of just 4 node extensions. The TS-SSD-ME algorithm obtains a loss of about 1 dB as compared to the FER of the maxlogAPP but at a complexity of approximately 27 times less than maxlogAPP. In case of TS-SSD-ME algorithm, the average number of node extension is 208 at $E_{\rm b}/N_0 = 21$ dB. Figure 5 also depicts the effect of iterative detection and decoding. The iterations between detector and decoder (4 iterations) leads to a performance improvement of approximately 4.5 dB in maxlogAPP which is approximately 1 dB more than the performance of iteratively applied TS-SSD-ME algorithm but at a complexity which is approximately 17 times higher than TS-SSD-ME algorithm. Figures 6 and 7 respectively show the results for Extended Vehicular A and Extended Typical Urban A. In both of cases the TS-SSD-ME algorithm gives performance close to maxlogAPP and at much reduced complexity. The shift of the FER curves towards lower $E_{\rm b}/N_0$ in case of EVA and ETU channels as compared to EPA is due to high correlation setup of the EVA channel.

In addition to this obvious reduction in complexity, the TS-SSD-ME algorithm enables an adjustment of complexity and FER performance by adaptation of the tuple size. This is very important both for detection performance and hardware implementation. For detection this allows to adapt the performance and complexity reaching from close to hard output (searching only ML point) to full LSD [5]. For hardware implementation this allows to minimize power consumption by adjusting tuple size according to variations in channel conditions.

VII. CONCLUSION

In this paper, we have provided performance and complexity comparison of the TS-SSD-ME MIMO detection algorithm for 3GPP LTE systems. We have shown how the complexity of the detection is reduced without significant performance loss by using TS-SSD-ME algorithm. This algorithm also enables high performance SISO detection at low complexity and allows flexible adaptation of the complexity and the achievable performance over the tuple size of a given detector. It fits the "one node per cycle architecture" with only 3 metric calculation without sorting. The metric calculation itself is simplified leading to a cycle latency reduced approximately to $\frac{1}{4}$ as compared to state of the art. Complexity of its potential hardware implementation is reduced by the smaller list needed, the reduction of information to be stored, less operations needed for the list maintenance and simplified L-value calculation. Low hardware implementation enables high detection speed applicable for mobile systems specifically 3GPP LTE.

In summary, it has been shown that at a reasonable complexity, a detection close to maxlogAPP is feasible for 3GPP LTE systems with TS-SSD-ME algorithm.

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