Signal Processing 125 (2016) 249–260

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Maximum likelihood soft-output detection through Sphere Decoding combined with box optimization

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ARTICLE INFO

Article history:
Received 3 November 2015
Received in revised form
1 February 2016
Accepted 3 February 2016
Available online 10 February 2016

Keywords:
MIMO
Soft-output maximum likelihood detection

ABSTRACT

This paper focuses on the improvement of known algorithms for maximum likelihood soft-output detection. These algorithms usually have large computational complexity, that can be reduced by using clipping. Taking two well-known soft-output maximum likelihood algorithms (Repeated Tree Search and Single Tree Search) as a starting point, a number of modifications (based mainly on box optimization techniques) are proposed to improve the efficiency of the search. As a result, two new algorithms are proposed for soft-output maximum likelihood detection. One of them is based on Repeated Tree Search (which can be applied with and without clipping). The other one is based on Single Tree Search, which can only be applied to the case with clipping. The proposed algorithms are compared with the Single Tree Search algorithm, and their efficiency is evaluated in standard detection problems (4×4 16-QAM and 4×4 64-QAM) with and without clipping. The results show that the efficiency of the proposed algorithms is similar to that of the Single Tree Search algorithm in the case 4×4 16-QAM; however, in the case 4×4 64-QAM, the new algorithms are far more efficient than the Single Tree Search algorithm.

1. Introduction

Digital communications using Multiple-Input Multiple-Output (MIMO) systems have nowadays been receiving considerable attention. These systems are included in current and future wireless communication standards, such as IEEE 802.11ac [1], Wimax [2] and 3GPP Long Term Evolution Advanced [3].

In MIMO systems, the use of soft-output detectors that are concatenated with a soft-input channel decoder can significantly improve the performance of wireless communications. A soft-output detector provides the reliability information of the received coded bits expressed as log-likelihood ratios (LLRs). These soft values are used by the channel decoder to carry out the final decision on the values of the received coded bits. However, the use of soft detection techniques involves a considerable increase in the computational cost compared with hard detection techniques, especially at low signal-to-noise ratios (SNR). This is so because soft detection methods require many more metric computations than hard detections methods. Practical applications of this technology will only be possible if efficient algorithms are developed.

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http://dx.doi.org/10.1016/j.sigpro.2016.02.006
0165-1684/

The MIMO detection algorithms that compute the maximum likelihood solution of the problem are known as maximum likelihood (ML) algorithms. In hard-output detection, demodulators based on the tree search strategy show a lower complexity than those based on exhaustive search, with the Sphere Decoding (SD) variants being the family of algorithms that is most commonly used [4–9]. Recently, a new hard-output SD ML algorithm was proposed in [10], where the SD algorithm was combined with box optimization. The results obtained were remarkably faster than other known hard-output ML detectors.

There exist several soft-output detection algorithms that use hard-output SD (or variations of it based on tree search) to compute the LLRs. Some of these soft-output algorithms are *Repeated Tree Search* (RTS) [11], a modified RTS algorithm [12], *Single Tree Search* (STS) [13,14], the *List-based SD* (LSD) scheme [15], *Soft-output Fixed-complexity SD* (SFSD) [16], the *Smart Ordering and Candidate Adding* (SOCA) algorithms [17], and *Soft-output K-Best* [18,19]. There are other soft-output detection methods that are not based on tree search, such as the method based on partial marginalization [20], the *SUMIS* method [21], soft-output detection based on *Minimum Mean Square Error–Parallel Interference Cancellation* (MMSE–PIC) [22], soft-output based on belief propagation and on factor graphs [23], and a conjugate-gradient method for precoding [24]. Another soft-output ML detector (similar to STS) including several optimizations was proposed in [25]. Some of these algorithms provide exact max-log LLRs (STS and RTS among them), while others (like the LSD or the SFSD algorithms) provide approximations to the max-log LLRs (this entails a certain loss of performance). Since the computational complexity of soft-output algorithms that compute exact max-log LLRs (soft ML algorithms) is too high, in practical applications the complexity must be reduced further through the use of clipping [26].

It must be mentioned that max-log LLRs are approximations to exact LLRs, and some methods may compute LLRs more accurately than with the max-log approximation. However, the max-log approximation is still the most popular form of computing LLRs. In the following we will speak of soft-output ML algorithms as algorithms that compute exactly max-log approximations to LLRs.

The RTS and STS algorithms are the best known soft-output ML algorithms. These algorithms are thoroughly discussed in [13,14], including the application of clipping to both algorithms. These papers show that STS is more efficient than RTS, thus making it one of the most efficient algorithms for soft-output ML MIMO detection (the version without clipping has been included in the Matlab communications toolbox [27]).

The work described in this paper has as its main goal the improvement in efficiency of soft-output ML detection algorithms, while at the same time preserving the ML property. We have obtained several possibilities for enhancing the RTS and STS algorithms.

We propose three alternative implementations: two based on RTS (for the cases with and without clipping) and another one based on STS which is only valid for the case with clipping. Some of the modifications proposed are based on the hard ML detector described in [10], while others can be implemented using any hard ML detector.

The algorithms obtained will be compared with the RTS and STS algorithms. The comparison of detection algorithms would usually be carried out in terms of efficiency and accuracy. However, since we are comparing soft-output ML algorithms, the accuracy comparison is not needed. This is because any soft-output ML algorithm implemented without clipping (such as STS, RTS or the algorithms proposed in this paper) will obtain the same exact max-log LLRs. The accuracy of MIMO detection methods is usually assessed through plots of Bit Error Rate (BER) against SNR. Therefore, since any two soft-output ML methods obtain the same max-log LLRs, the BER plot of both methods would be exactly the same line.

The same occurs when two soft-output ML methods implemented with clipping are compared (using the same clipping parameter). Since the max-log LLRs obtained are exactly the same, any plot for evaluation of accuracy would produce exactly the same line for both methods; such a plot would not convey any interesting information. The accuracy comparison is relevant when non-ML soft-output methods are compared with ML soft-output methods. However, this would be out of the scope of this paper and has been studied in other papers such as [13] and [17]. In this paper, we concentrate only on comparing different soft-output ML detection methods, and, therefore, we focus on comparing the efficiency of the methods.

In the following, we first describe the problem at hand and the algorithms to be applied or modified, and then we evaluate the resulting algorithms numerically, comparing their efficiency with the STS algorithm.

2. Problem description

Let us consider a MIMO-Bit Interleaved Coded Modulation (BICM) system (described graphically in Fig. 1) with m transmit antennas and n receive antennas ($n \geq m$). In this system, the sequence of information bits is encoded using an error-correcting code and is passed through a bitwise interleaver before being demultiplexed into m streams. In each stream, the bits are mapped into a complex symbol s_i, which is taken from a constellation $\Omega \subset \mathbb{C}$ of size $|\Omega| = L$ and hence carrying $q = \log_2 L$ code bits each. The transmit symbol vector is given by $\mathbf{s} = (s_1, \ldots, s_m)^T$, and the associated complex baseband model for the received vector can be written as

$$\mathbf{y} = \mathbf{H} \cdot \mathbf{s} + \mathbf{v}. \tag{1}$$

Here, $\mathbf{H} \in \mathbb{C}^{n \times m}$ is the MIMO channel matrix with independent elements $h_{ij} \sim \mathcal{CN}(\mathbf{0}, \mathbf{1})$ and $\mathbf{v}$ denotes a white-Gaussian noise (AWGN) complex vector with elements $v_i \sim \mathcal{CN}\left(\mathbf{0}, \frac{\mathbf{N_0}}{2}\right)$.

The MIMO detection problem can then be stated as:

$$\mathbf{s}^{\mathrm{ML}} = \arg\min_{\mathbf{s} \in \Omega^m \subset \mathbb{C}^m} \|\mathbf{H} \cdot \mathbf{s} - \mathbf{y}\|^2. \tag{2}$$

The hard ML solution to the MIMO detection problem is the vector $\mathbf{s}^{\mathrm{ML}}$. Throughout this paper, given a possible