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Congestion control based ant colony optimization algorithm for large MIMO detection

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A B S T R A C T

Employing multiple antennas in wireless communication systems is a key technology for future generation of wireless systems. Symbol detection in multiple-input multiple-output (MIMO) systems with low complexity is challenging. The minimum bit error rate (BER) performance can be achieved by maximum likelihood (ML) detection. However, with increase in number of antennas in MIMO systems, the ML detection becomes impractical. For example, sphere decoder (SD) is a well known ML detector for MIMO systems, however because of its high complexity it is practical only up to 32 real dimensions. Recently, bio-inspired algorithms are being used for improving the BER performance of MIMO symbol detector, along with low complexity. In this article, we propose a congestion control based ant colony optimization (CC-ACO) algorithm for large MIMO detection. We also discuss the robustness of the proposed algorithm under channel state information (CSI) estimation error. The simulation results shows the effectiveness of the proposed algorithm in terms of achieving better bit error rate (BER) performance with low complexity.

1. Introduction

With the rapid growth in wireless technology, the demand for data rates is increasing exponentially. To meet this throughput demand, communication technology is moving towards employing multiple antenna systems. Significant data rates can be achieved by employing MIMO systems (Foschini & Gans, 1998; Telatar, 1999) without the need of additional spectrum. The key idea behind this is spatial multiplexing through which multiple data streams can be transmitted simultaneously. A higher spectral efficiency can be achieved using large MIMO (MIMO systems with large antennas) (Chockalingam & Rajan, 2014). As the number of antennas increases the number of computations required at the receiver increases rapidly and the optimal detection of the transmitted signal becomes practically infeasible (Paulraj, Nabar, & Gore, 2003). This motivates research in devising low complexity sub-optimum algorithms. The well known sub-optimum linear detectors include zero forcing (ZF) detector, minimum mean squared error (MMSE) detector and non linear detectors like vertical Bell laboratories layered architecture (V-BLAST) detector (Wolniansky, Foschini, Golden, & Valenzuela, 1998), successive interference cancellation (SIC) based MIMO detection algorithms (Lee et al., 2006; Wübben, Rinas, Böhnke, Kühn, & Kammeyer, 2002). Minimum bit error performance can be achieved by using maximum likelihood (ML) detection, but it becomes a non-deterministic (NP) hard problem for large MIMO systems (Chockalingam & Rajan, 2014). ZF, MMSE and VBLAST are low complexity MIMO detection techniques but are inferior in performance when compared to ML performance. Therefore, the focus is on searching a reasonable approximate solution with lesser complexity. Other algorithms for large MIMO detection includes multistage likelihood ascent search (M-LAS) algorithm (Mohammed, Chockalingam, & Sundar Rajan, 2008) which performs a sequence of LAS algorithm (Vardhan, Mohammed, Chockalingam, & Rajan, 2008) for symbol detection. Random restart reactive tabu search (R3TS) algorithm (Datta, Srinidhi, Chockalingam, & Rajan, 2010) is another such algorithm where parallel search stages of reactive tabu search algorithm (Rajan, Mohammed, Chockalingam, & Srinidhi, 2009) are initialized with random initial points to avoid convergence to a local minima. The performance of the algorithms proposed in Rajan et al. (2009) shifts away from the optimal solution with increase in modulation order. Another large MIMO detection algorithm includes belief propagation (BP) based detection algorithm (Som, Datta, Chockalingam, & Rajan, 2010) which is graphical method based detection algorithm, but the performance of the algorithm degrades for higher order modulation. In this

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article, our objective is to provide a low complexity large MIMO detection algorithm for higher order modulation.

In recent years, bio-inspired optimization algorithms have been a topic of great interest for signal processing researchers. Moreover, these algorithms involve less mathematics and provide sub-optimum solution with low complexity. Some of these algorithms are genetic algorithm (GA), particle swarm optimization (PSO) and ant colony optimization (ACO) algorithm. All these algorithms are evolutionary computation techniques which are used for low complexity applications and are useful for optimizing the non-deterministic polynomial (NP) hard problems. Some applications of GA and PSO algorithms are given in Das, Pattnaik, and Padhy (2014), Ahmad, ichi Azuma, and Sugie (2014), Majhi and Panda (2010), Chandwani, Agrawal, and Nagar (2015), Changdar, Mahapatra, and Pal (2015). An overview of GA based detection for MIMO systems is addressed in Jiang and Hanzo (2007). However, there are some deficiencies with GA. The performance of GA is degraded by premature convergence which reduces its search ability (Fogel, 2006). PSO has also been applied successfully in MIMO detection in Khan, Naeem, and Shah (2007b). However, with increase in number of antennas and modulation order in MIMO systems, the number of particles in PSO based detection has to be increased, which inturn increases complexity of the algorithm. This results in performance-complexity tradeoff. To overcome the problem of premature convergence in GA and performance-complexity tradeoff in PSO, we present an alternate approach using congestion control based ACO (CC-ACO) algorithm for MIMO detection.

Ant colony optimization (ACO) is based on the foraging behavior of real ants (Dorigo & Birattari, 2010). There are many applications of ACO available in the literature, some of which are given in Dorigo and Gambardella (1997), Wu, Zhao, Ren, and Quan (2009), Deng and Lin (2011), Filho, de Souza, and Abro (2012). In this article, we will use the concept of ACO for symbol vector detection in MIMO systems at the receiver. Similar work has been done in Khurshid, Irteza, and Khan (2010), Khan, Bashir, Naeem, Shah, and Sheikh (2007a), Lain and Chen (2010), Marinello and Abrão (2013). The algorithm in Khurshid et al. (2010) provides a detection scheme for BPSK modulated MIMO systems and the results obtained are sub optimal in performance. In Khan et al. (2007a) the performance curve shifts away from ML solution with higher number of antennas and experiences diminishing returns, which makes it unsuitable for large MIMO detection. The work in Lain and Chen (2010) does not provide ordering in the detection sequence and requires a large number of ants (20,000 ants) to converge towards ML solution which increases the complexity. The modified ACO (MACO) algorithm in Lain and Chen (2010) assume the ants to find the solution independently i.e. no pheromone based interaction and the probability metric depends only on the heuristic value. In Marinello and Abrão (2013), the authors proposed a lattice reduction aided ACO detector for MIMO communication where the ACO heuristic approach is coupled with the lattice reduction (LR) technique. New pheromone technique for pheromone update scheme has been proposed and a significant improvement in terms of performance-complexity tradeoff has been shown. However, the LR-ACO algorithm requires an initial guess to start with, which adds to the complexity of LR-ACO algorithm. A comparison based on the advantages and drawbacks of different MIMO detection algorithms discussed is given in Table 1.

In this article, we propose a CC-ACO algorithm for large MIMO detection. In CC-ACO, we allow a set of artificial ants to jointly find a solution. We use the concept of negative pheromones for congestion control based scheme to avoid premature convergence to a local optimum solution. The advantage of the proposed algorithm is two fold: 1. Congestion control based ACO which avoids premature convergence to a local optimum solution, and 2. Ordering sequence in detection which further improves the solution by minimizing the error propagation while detecting the symbols sequentially. We will investigate the performance of the proposed CC-ACO algorithm for different number of antennas and also compare our results with the MMSE equalizer and the unordered ACO algorithms. The results show that for the given number of ants, the proposed algorithms outperforms MMSE and unordered ACO. To validate the robustness of the proposed algorithm, we discuss the performance of our CC-ACO algorithm under channel state information (CSI) estimation error conditions.

The rest of the paper is organized as follows. In Section 2, we present the general ACO algorithm. System model and mathematical formulation are given in Section 3. ACO based MIMO detection algorithm is discussed in Section 4. In Section 5, we present the simulation results for BER performance versus signal to noise ratio (SNR), convergence analysis curve for BER performance versus number of ants (N_{ants}) and the complexity curve for number of computations versus N_{ants} and the number of antennas respectively. Section 6 concludes the paper.

2. Ant colony optimization

In this section, we provide an overview of ACO technique which was originally proposed by Dorigo and Birattari (2010). In ACO, we use a number of artificial ants (N_{ants}) to find a shortest path between their nest N and the food location F as shown in Fig. 1. Ants use the phenomena known as stigmergy, which means communication through environment. When ants walk to and fro between N and F, they deposits on ground a substance called *pheromone* on each path. The pheromone concentration on each path decays with time and the ants always choose the path with higher pheromone concentration. Starting from N, the ants which chose the shorter path will reach F quickly, and hence in the return journey it will find the pheromones only on the shorter path. This selection of path for return journey further increases the pheromone concentration on the shorter path. ACO is an iterative algorithm, hence, in each iteration ants deposit pheromones on the path they walk. Each ant checks the quality of pheromones present due to the previous iterations for selecting a path. After sufficient number of iterations, all ants will start selecting the shorter path and the algorithm thus converges. The three basic steps followed in ACO algorithm are shown in Algorithm 1.

Algorithm 1. Ant colony optimization algorithm

```
procedure
    Initialize the system parameters
    while termination condition not met do
      Construct Ant Solutions
      Apply Local Search
      Update Pheromone Concentration
    end while
end procedure
```

Construct Ant Solutions: A set of artificial ants construct a solution based on the given parameters in the initialization step. The partial solution is extended by adding a feasible solution component at each step. This process of constructing ant solution can be regarded as a walk on the available paths. Choice of a path is guided by stochastic selection which is based on pheromone concentration on the path.

Apply Local Search: Once the solutions have been constructed, a local search process will be initialized to improve the solution. During this process, the best of the available solution is selected