Ant Colony Optimization for Joint Channel Estimation and Impulsive Noise Mitigation Method in OFDM Systems

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Abstract –

The impulsive noise can deteriorate sharply the performance of orthogonal frequency division multiplexing (OFDM) systems. In this paper, we propose a novel joint channel impulse response estimation and impulsive noise mitigation algorithm based on compressed sensing theory. In this algorithm, both the channel impulse response and the impulsive noise are treated as a joint sparse vector. Then, the sparse Bayesian learning framework is adopted to jointly estimate the channel impulse response, the impulsive noise, and the data symbols, in which the data symbols are regarded as unknown parameters. In this article, we propose an ant colony optimization (ACO) algorithm for large MIMO detection analysis. We also discuss the robustness of the proposed ant colony algorithm for better enhancement and quality of analysis, the proposed algorithm utilizes all subcarriers without any a priori information of the channel and impulsive noise. The simulation results show that the proposed algorithm achieves significant performance improvement on the channel estimation and bit error rate performance.

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I. Introduction

In several applications of wireless communication technology (e.g., vehicular networks [1], smart grid [2], and shallow sea underwater networks [3]), the transmission of data signals will be severely deteriorated by impulsive noise (IN). The sources of impulsive noise are diverse, such as ignition noise in automobiles [4], switches for electrical equipment [5], various maritime operations [6], and so on. Compared to additive white Gaussian noise (AWGN), impulsive noise arises randomly with short-duration and high-power impulses. Orthogonal frequency division multiplexing (OFDM) technology has been widely adopted in most modern wireless communication standards [7]. In conventional OFDM receivers, the time-domain received signal is convertedinto the frequency domain through a discrete Fourier transform (DFT), after which each subcarrier is demodulated independently [8]. Such tone-by-tone demodulation achieves optimal maximum likelihood detection in AWGN and perfect channel state information [9]. When the impulsive noise is present, however, the corresponding frequency-domain noise samples will be highly dependent, and tone-by-tone demodulation is no longer feasible since the complexity of performing joint detection at the receiver increases exponentially with the number of subcarriers [10].

The efficient impulsive noise suppression method plays an important role in promoting the performance of OFDM communication systems in the presence of additive impulsive noise. Since the amplitude of the impulsive noise is usually much higher than the background noise, it is possible to determine the presence of impulsive noise by setting a threshold and then designing a memoryless nonlinear pre-processor (e.g., clipping, blanking, or a combination thereof) toeliminate the effect of impulse noise [11]–[14]. By setting multiple thresholds, the nonlinear estimator for impulsive noise can improve the signal-to-noise power ratio (SNR) at the receiver [15]. However, these methods require the noise prior statistics to obtain the optimal threshold but suffer from performance degradation when the priori information mismatches the time-varying noise statistics, which is not easy to acquire in reality as well. Moreover, this nonlinear pre-processor may destroy orthogonality among OFDM subcarriers, thus resulting in intercarrier interference in the frequency domain [16]. Recently, there has been growing interest in developing compressed sensing (CS) based impulsive noise mitigation methods that exploit the time-domain sparsity of impulsive noise [4], [6]. These methods all make use of the information of null tones (i.e., tones that do not carry data or pilots) of the received OFDM symbol to estimate the IN sample and then subtract it from the received signal. Furthermore, some of them have been extended for detecting bursty (i.e., block sparse) impulsive noiseby using structured compressed sensing theory. Although these methods show obvious advantages over those based on nonlinear pre-processors, the common drawback of these algorithms is that their performances are mostly limited by the number of null tones. It is worth pointing out that these approaches also assume that the channel state information is already estimated perfectly before the impulsive noise removal and do not consider the severe impact of impulsive noise on the channel estimation. The performance of the IN estimator can be improved by increasing the number of null tones. However, having more null tones means reduced throughput. When the number of null tones is limited, it is desirable to exploit the information available in all tones to improve the estimation performance of the impulsive noise. The difficulty in exploiting all tones, however, is how to simultaneously estimate the channel and impulsive noise. An approach for jointly estimating channel and IN is proposed but it requires that there is no overlap between the support of impulsive noise and channel impulse response. iterative channel estimation and impulsive noise mitigation algorithm are proposed on the assumption that the length of the channel impulse response is known in advance and that the channel is static for several OFDM symbols. generalized approximate message passing (GAMP)has been used to jointly estimate the channel taps, the impulse noise samples, symbols, and the unknown bits. This method requires the acquisition of a priori information of the channel and impulsive noise and does not offer rigorous convergence although it is lower in computational complexity. By assuming that the impulsive noise parameter distributions are known at the receiver, joint channel estimation and data decoding algorithmsare developed [30]. By exploiting the sparsity of both of them, the orthogonal matching pursuit(OMP) is adopted for joint channel and impulsive noise estimation in underwater acoustic OFDM systems. This algorithm needs to collectthe number and position of IN samples by applying a blanking operation.

In this paper, we propose two novel algorithms based on the Sparse Bayesian Learning (SBL) framework to jointly estimate both the channel impulse response and impulsive noise by exploiting the sparsity of both of them. Our algorithms can also be categorized as an extension of the method proposed. The first proposed method uses the pilot subcarriers to jointly estimate the channel impulse response and impulsive noise. Once the channel and IN are estimated, the IN is then removed from the received signal and the channel is transformed into the frequency domain followed by the channel equalization. In the second proposed algorithm, we utilize both the data and pilot subcarriers to promote the joint estimation performance of the channel impulse response and impulsive noise. Compared with the algorithms which treat the channel estimation and IN mitigation independently, our proposed joint estimation algorithms can lead to a significant improvement in the ant colony optimization (ACO) of channel estimation. For impulsive noise mitigation, our method using all subcarriers has a smaller Mean Square Error (MSE) of IN estimation than existing impulsive noise mitigation algorithms using only the null subcarriers.

The contributions of this paper are as follows:

• We treat the unknown data symbols as the hyperparameters and develop an iterative technique based on the Expectation Maximization ant colony optimization (ACO) algorithm for joint channel estimation, IN estimation, and data detection. Our algorithm can efficiently recover a sparse vector even when the measurement matrix is partially unknown due to the presence of unknown data symbols.

• Being different from many CS based IN estimation methods that use only the null subcarriers, our proposed method can exploit all subcarriers to improve the IN estimation performance. Our methods need fewer null subcarriers and can promote spectrum efficiency. Apart from the assumption that the channel impulse response and impulsive noise samples are all sparse, our proposed methods do not require other prior information.

• We derive the closed-form ant colony optimization (ACO) of the channel and impulsive noise estimation.

II. Survey On Ant Colony Optimization

ACO was proposed by Marco Dorigo in 1992 in his Ph.D. Thesis. The model proposed by Deneubourg and coworkers for explaining the foraging behavior of ants was the main source of inspiration for the development of ant colony optimization [9]. Ant colony optimization is based on the technique known as Swarm Intelligence, which is a part of Artificial Intelligence. Artificial Intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs.

III. Proposed Work

Ant Colony Optimization (ACO) is a metaheuristic approach for solving hard combinatorial optimization problems. The inspiring source of ACO is the pheromone trail laying and following behavior of real ants which use pheromones as a communication medium. In analogy to the biological example, ACO is based on the indirect communication of a colony of simple agents, called (artificial) ants, mediated by (artificial) pheromone trails. The pheromone trails in ACO serve as distributed, numerical information which the ants use to probabilistically construct solutions to the problem being solved and which the ants adapt during the algorithm's execution to reflect their search experience [11]. A classic example of the construction of a pheromone trail is the search for a path between food and a nest established by the ants. In Figure 1 an obstacle is inserted into the path. Soon, ants spread to both sides of the obstacle, since there is no clear trail to follow. As the ants go around the obstacle and find the previous pheromone trail again, a new pheromone trail will be formed around the obstacle.

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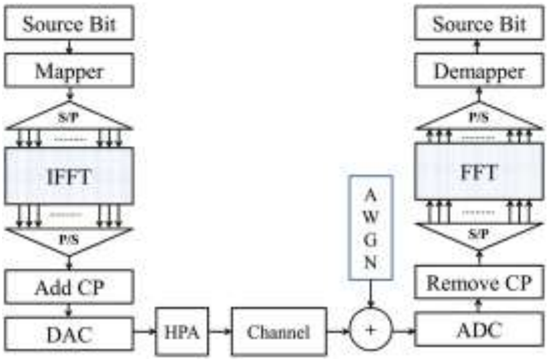

Figure 1: Conventional OFDM system

First of all, the searching graph of the discrete power allocation problem should be designed for the ants to move from node to node to construct solutions. In this paper, each cell creates a searching graph for ants to allocate power for the subchannels. Since the multi-cell power allocation problem is more complex than a typical NP-hard problem, like TSP, the conventional ACO is improved in that ant colonies of each cell cooperate to maximize the whole system throughput. The searching graph of each cell is shown in Fig. 1, which is a two-dimensional graph consisting of L × M nodes. The Column denotes M subchannels, andthe row denotes L power levels, thus each node represents a subchannel and power level pair. Virtual nest and food are located on both sides of the graph. Artificial ants start from the nest and move from one column to another to select power level for the subchannels until food resource is found. The size of the nodes represents the pheromone amount, and at the beginning of the algorithm, the pheromone amount for all the nodes is initialized to an equal const value τ0. By continually changing the size of the nodes while ants move, ACO can obtain satisfied feasible solutions.

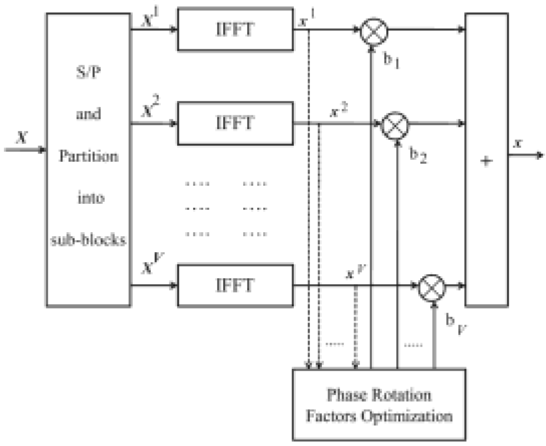

Figure 2: The ACO method in OFDM systems

Pheromone is not the only factor that the ants depend on to construct solutions to the target problem, heuristic information also plays an important role when the ants chose the next step. Similar to the visibility of ant in TSP, this information measures the quality of nodes that can be added to the current partial solution. The bigger the heuristic information of the node is, the more possibleit to be selected. Power allocation strategies of adjacent cells influence each other, high power level producesa high data rate of the specific cell, but causes serious interference to neighbor cells. Hence, to attract the ants to findglobally optimal solutions, the performance of cochannel cells is also taken into consideration in the calculation of the heuristic information.

$$R_{l,m} = \sum_{j=1}^{I} r^{j}_{m,k}(\mathbf{P}_m | P^{i}_{m} = \varepsilon_l)$$

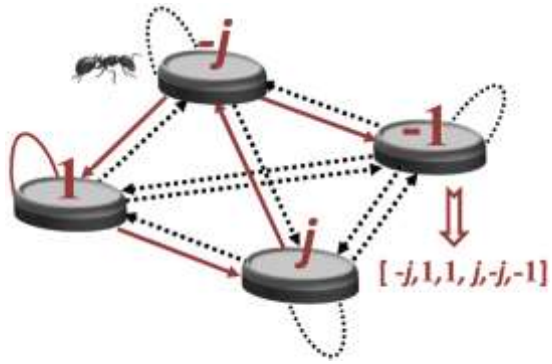

Figure 3: The graph representation for phase factors selection

At each iteration, an artificial ant is dispatched from the nest to find a possible solution for the cell, and the computation of each cell runs independently. The ants choose the power level for the subchannel by traveling in the searching graph according to a pseudorandom proportional rule which offers a tradeoff between "exploitation" and "biased exploration".

$$l = \begin{cases} \arg\max_{k\in[1,2,\cdots,L]}([\tau_{k,m}]^{\alpha}[\eta_{k,m}]^{\beta}), & \text{if } q \le q_0 \\ J, & \text{else} \end{cases}$$

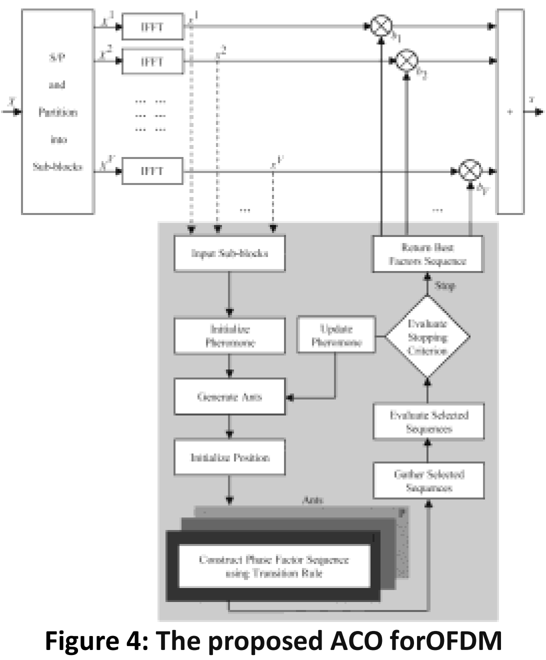

Figure 4: The proposed ACO forOFDM

Local pheromone updating can reduce the pheromone amount and improve the possibility of other nodes beingselected by the ants. In this way, the algorithm will not slide into stagnation, which means the ants will not select the same path, and this is effective for the situation when power exceeds constraint. Global pheromone updating is based on the information exchange between ant colonies of different cells. Once all theant colonies of different cells finished the power allocation for their subchannels, a new power allocation strategy is gathered from different cells and compared with the best-so-far solution. The one which can provide larger system throughput will be the new best-so-far solution. And the global pheromone updating is applied only on the nodes indicated by the best so-far solution.

$$\tau_{l,m} = (1-\rho)\tau_{l,m} + k_0 \rho R$$

where ρ is the global evaporation rate, and k0 is a const parameter to adjust the amount of pheromone to be released. We can see from (11), that the better the solution is, the more pheromone is gained on the nodes of the path. Furthermore, the new best-so-far solution is passed on to each colony. After the construction of global pheromone updating, one time of iteration is finished. If the condition of iteration ends is satisfied, for instance reaching the pre-determined maximal iterative time, the algorithm will be finished and the power is allocated based on the best-so-far solution. The proposed ACO-based algorithm can be summarized.

IV. Simulation Results

In this section, we demonstrate the performance of the proposed joint channel estimation and IN estimation algorithms through Monte Carlo simulations. We consider a 3 MOFDM system with 256 subcarriers.

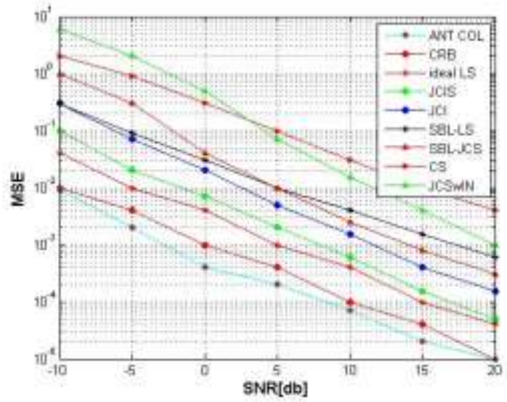

Figure 5. The MSE of channel estimation versus SNR. The number of pilot subcarriers is 44. The number of null subcarriers is 50.

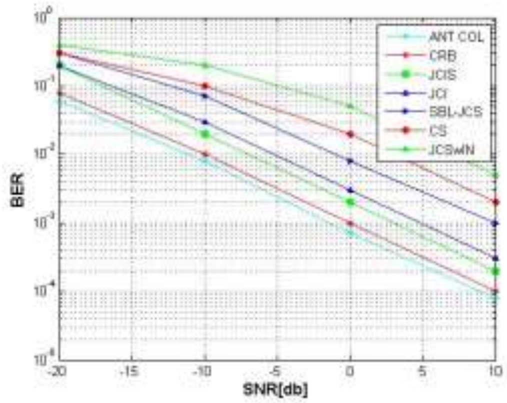

Figure 6. The MSE of channel estimation versus SNR. The number of pilot subcarriers is 64. The number of null subcarriers is 50.

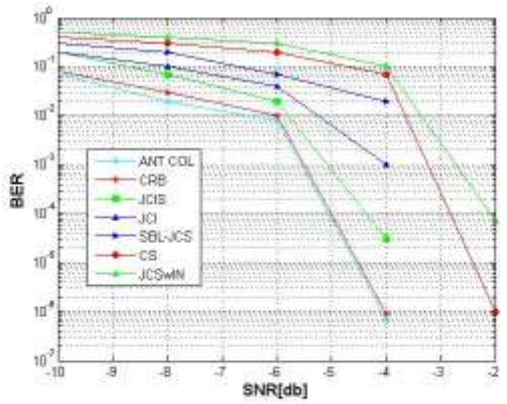

Figure 7.The MSE of IN estimation versus SNR. The number of null subcarriers is 50. The number of pilot subcarriers is 44.

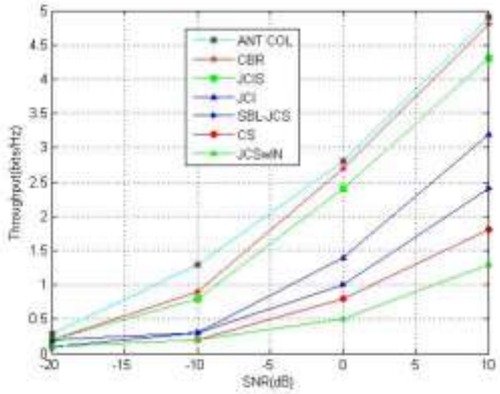

Figure 8. The MSE of IN estimation versus SNR. The number of null subcarriers is 100. The number of pilot subcarriers is 44.

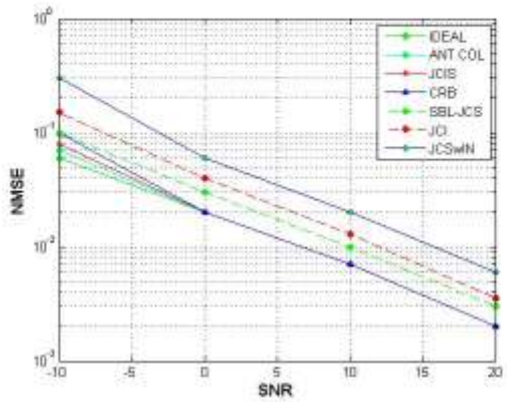

Figure 9. BER versus SNR in uncoded OFDM system. The number of pilot subcarriers is 44. The number of null subcarriers is 50.

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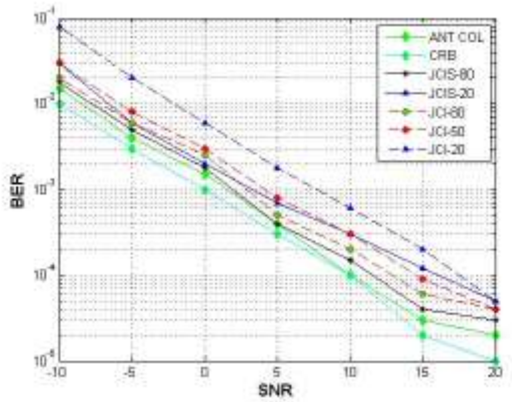

Figure 10. BER versus SNR in coded OFDM system. The number of pilot subcarriers is 44. The number of null subcarriers is 50

V. Conclusion

In this paper, we consider joint sparse channel estimation, impulsive noise mitigation, and data detection for OFDM systems. By observing the sparsity of channel and impulsive noise in the time domain, we construct an expanded sparse vector to represent the channel and impulsive noise together. To estimate the augmented vector, the JCI algorithm is proposed which uses only the pilot and null subcarriers. Furthermore, JCIS algorithm is developed to improve the performance of channel estimation and impulsive noise cancelation, which apply the data detection simultaneously. We derive the analytical expression of BCRB for the ACO algorithm as well. The MSE performance of our proposed scheme outperforms the conventional methods and is close to the lower bound. Moreover, simulation results show our methods can have a good BER performance with fewer pilot and null subcarriers and obtain better spectral efficiency.

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