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Original scientific paper

Channel Estimation in MIMO TFT-OFDM Using Hybrid BESOA- CSOA Algorithms

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Abstract: In wireless communication systems, maximizing spectral efficiency and enhancing link reliability are key objectives. One effective solution is the combination of Orthogonal Frequency Division Multiplexing (OFDM) and Multiple-Input Multiple-Output (MIMO) techniques. OFDM divides the frequency band into non-overlapping sub-bands, enabling parallel data transmission. This helps overcome the limitations of traditional wireless communication systems with high-rate input data streams. MIMO-OFDM has emerged as a promising technology for achieving high data rates and robustness in wireless communications by supporting multiple inputs and outputs. However, optimizing both spectral efficiency and performance in rapidly fading channels can be challenging. To address these issues, we propose Time Frequency Training Orthogonal Frequency Division Multiplexing (TFT-OFDM). This approach utilizes group pilots for spectrum efficiency and shared channel estimates to maintain system performance stability. Channel estimation plays a critical role in TFT-OFDM, and both Least Square (LS) and Minimum Mean Square Error (MMSE) methods are considered. LS estimation has a simple approach but lower performance, while MMSE significantly reduces mean square error at the cost of computational complexity. To estimate the channel in TFT-OFDM, joint time and frequency channel estimation techniques are employed. This involves using sophisticated algorithms to optimize parameters such as maximum or minimum function values in the solution space. The intelligent algorithms, specifically the Bald Eagle Search Optimization (BESOA) technique and the Cat Swarm Optimization Algorithm (CSOA), are utilized to estimate the channel efficiently in spectrally efficient MIMO-OFDM wireless networks. Performance improvement is observed with the intelligent algorithms. For instance, at a signal-to-noise ratio (*SNR*) of 15 dB, the proposed BESOA method achieves a Bit Error Rate (*BER*) of 10^{-6}, while TFT-OFDM with group pilots achieves a *BER* of 10^{-3}, and conventional CP-OFDM yields a *BER* of 10^{-2}. Furthermore, the CSOA method outperforms the Firefly Algorithm in terms of *BER* performance.

Keywords: Bald Eagle Search Optimization technique; Cat Swarm Optimization Algorithm; MIMO; OFDM; Time Frequency Training Orthogonal Frequency Division Multiplexing

1 INTRODUCTION

Multi-input, multi-output (MIMO) technology has garnered interest in the telecommunications sector due to its potential to boost data transmission rates without increasing either the required bandwidth or the transmit power. Improvements in OFDM performance are expected thanks to recent advances in MIMO methods. The performance advantages of OFDM technology are achieved by delivering data independently from many antennas, which necessitates a large number of antennas at both ends of the wireless networks [1]. The MIMO-OFDM combines MIMO with orthogonal frequency division multiplexing, which greatly simplifies equalisation in MIMO systems and allows for the inclusion of additional antennas.

Enabling MIMO-OFDM combines MIMO with orthogonal frequency division multiplexing, which significantly simplifies equalisation in MIMO systems and allows for the inclusion of additional antennas. Integration of MIMO and Orthogonal Frequency Division techniques MIMO OFDM systems, which use multiplexing technology, allow for data speeds for indoor wireless systems of hundreds of Mbps and spectral efficiency of tens of bits/Hz/s, both of which would be impossible with traditional single-input single-output systems [2].

In order to implement MIMO-OFDM with N subcarriers, separate data streams must first undergo IFFT at the OFDM modulators, then undergo parallel-to-serial conversion. The transmitted OFDM symbols have a cyclic prefix appended to them before being sent to the OFDM demodulators, where the CP is removed and an N-point FFT is performed. The OFDM demodulators' primary outputs are isolated and decoded. The MIMO systems provide potential answers to the dilemma of rising requirements for high-quality, high-bit-rate communication [3]. The receiver's ability to recognise the broadcast signal efficiently depends on its familiarity with Channel State Information.

Secure information for coherent detection of message symbols is a difficulty in MIMO-OFDM systems. Different estimation procedures, including as training-based, blind, and semi-blind estimation of the channel, are used to estimate the channel's state. The only-receiver knows-what-they're-doing blind estimate is used for teaching symbols or pilot tones. In order to estimate the channel, these training symbols are multiplexed with the data stream. To achieve channel estimate, semi-blind methods use a mix of traditional blind channel estimation plus training using pilot carriers [4]. Such pilot sequences are the unmodulated data which transmit data, and such pilots are used for the estimation of a channel and its synchronization. There are more pilots that are efficiently estimated and can increase the capacity of the channel. But the increase in the pilot also increases the overhead. The MIMO-OFDM scheme that is spectrally efficient will be identified as the TFT-OFDM.

2 RELATED WORKS

In case of the CP-OFDM and the ZP-OFDM schemes, the frequency domain pilots are used for performing a channel estimation, and this pilot is used for synchronization. The broadcasting standard DMB-T makes use of the TDS-OFDM scheme. As opposed to the Cyclic Prefix (CP), another known Training Sequence is inserted as the guard interval and used for the synchronization. When examined against the efficiency provided by CP-OFDM and ZP-OFDM, this method is superior by 10%. Channel equalisation, channel estimation, and this iterative process for cancelling out interference all depend on one another. The algorithm's low performance and great complexity will be shown in the situation of rapid fading channels. To get around this, the TFT-OFDM has been suggested [5-7].

TFT-OFDM is the abbreviation for Time and Frequency Training Orthogonal Frequency Division Multiplexing. It refers to the training sequence, in the Time domain, and the grouped pilots that are given within the frequency domain. The TFT-OFDM is an efficient scheme and the performance of which is better than other schemes. Time-frequency-division multiplexing (TFT-OFDM) employs a dual-domain approach to channel estimation. The estimated value of the channel route delay and parameters in the frequency domain primarily utilizes the capabilities of this Training Sequence (TS), which exists inside the time domain [8-11]. This interference caused by these TS may be removed in case the channel estimation is perfect. For an ideal estimation of the channel the OFDM data block will be random and unknown.

This issue of estimation is decoupled into the antennas. But in case of the enhanced training based techniques, the correlation among several antennas is considered. This does not mean that such enhanced methods of training in case of smaller subgroups will receive antennas that are not used or used as a means of another approach where the performance may not be similar [12-14]. An optimal method is found for this channel estimation, and this has a high computation cost.

There has been a recent rise in the widespread use of evolutionary algorithms like Particle Swarm Optimisation (PSO). However, the PSO's developments were mostly overlooked by digital communications journals. Here, there is an overview of an original PSO which is given with improvements that are applicable. As opposed to the determination of such average iterations that are required empirically, a new method for computing maximum iterations has been developed that can enable complexity evaluation for a varied range of parameters. The basic channel estimation techniques developed are Least Square and the Minimum Mean Square Error (MSE) [15, 16]. These findings are then used to two more evolutionary algorithms, the Genetic Algorithm (GA) and the Bacterial Foraging Optimisation (BFO), which optimise the estimated results. There is a compromise among the techniques Bit Error Rate (*BER*), MSE, and Signal to Noise Ratio (*SNR*) efficiency.

There are new techniques that have been formulated for checking their ability to cope up with the issues. Among these, some new algorithms like the Particle Swarm Optimization (PSO), the Cuckoo Search and the CSOA Algorithm (FA), have gained a lot of acclaim in view of their high level of performance. The computational engine (CE) has benefited greatly from the use of the Swarm Intelligence approach [17, 18]. Nevertheless, it suffers from the widespread issue of local optima. To address these problems, BESOA-CSOA heuristic is presented here for use in the CE.

The existing methods of data-aided channel estimation are Least Square (LS) and Minimum Mean Square Error (MMSE) methods which do not achieve a great performance. Moreover, MMSE is a little complex and has higher computational cost. That is why many attempts have been done previously to optimize the methods with help of meta heuristics and also other ways.

3 PROPOSED MIMO TFT-OFDM SYSTEM MODEL

Within the traditional CP-OFDM technique or the TDS-OFDM training, the data may be found in both the frequency domain or in the time domain. However, the TFT-OFDM method transmits training data in both the time and frequency domains. Each frame of the transmitted TFT-OFDM signal consists of a single preamble, its cyclic implication, and U subframes of TFT-OFDM signals. It presupposes a Multiple-Input Multiple-Output (MIMO) system equipped with *NT* transmitters and *NR* receivers. The proposed structure is shown in Fig. 1.

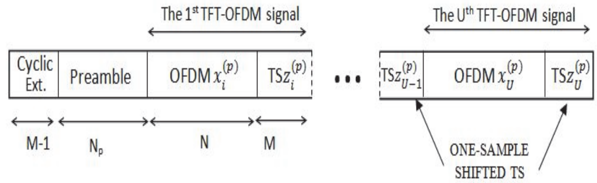

Figure 1 The proposed TFT-OFDM signal structure, TFT-OFDM with time and frequency domain training information

The channel tracking process for TFT-OFDM involves utilizing the time-frequency joint channel estimation method to derive the channel information from the time-frequency training symbol. This is achieved through a series of sequential steps. One possible topic of study is the utilization of time-series (TS) methodology for the estimation of path delay, a method of estimating path gain using pilot signals. Fig. 2 depicts the schematic representation of a joint estimation approach in the time-frequency domain.

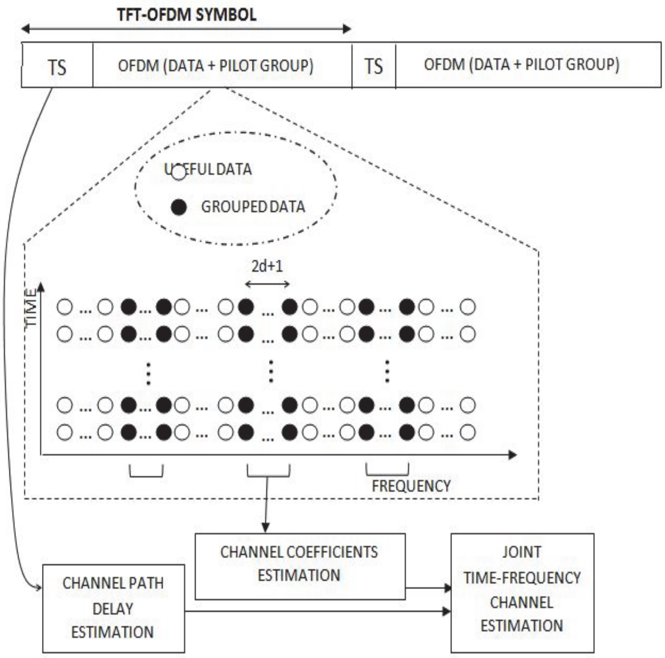

Figure 2 Time frequency joint channel estimation

3.1 Bald Eagle Search Optimization Algorithm (BESOA) Algorithm

An example of a naturally-inspired optimization algorithm, the Bald Eagle Search Optimization Algorithm (BESO) is modelled after the strategies used by bald eagles during their hunts. In place of time-honored optimization strategies, Dr. Seyedali Mirjalili introduced it in 2015. Bald eagles are known for their hunting ability, which involves scanning large areas of land for prey, then diving down to capture it with precision and speed. BESO mimics this behavior by iteratively searching for the best solution to an optimization problem.

The algorithm begins by randomly initializing a population of bald eagles, each of which represents a potential solution to the optimization problem. The eagles then search the solution space using a combination of global and local search strategies. The global search strategy involves randomly exploring the entire solution space, while the local search strategy involves focusing on the most promising solutions in the vicinity of the current best solution. During each iteration, the eagles update their positions based on their fitness, which is evaluated using an objective function that measures the quality of the solution. The best solution found by the eagles at the end of the search process is returned as the optimal solution to the optimization problem. BESO has been shown to be effective in solving a wide range of optimization problems, including continuous and discrete optimization problems, as well as multi-objective optimization problems. It has also been shown to be competitive with other popular optimization algorithms such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization. Overall, BESO is a promising optimization algorithm that offers a novel approach to solving complex optimization problems. Its ability to balance global and local search strategies makes it a versatile tool for a wide range of applications.

High-level flowchart of the Bald Eagle Search Optimization Algorithm:

Step 1: Initialize a population of bald eagles randomly.
Step 2: Evaluate the fitness of each eagle using an objective function.
Step 3: Set the current best solution as the eagle with the highest fitness.
Step 4: Repeat until a stopping criterion is met:
Step 5: Randomly select a subset of eagles to perform global search.
Step 6: Update the position of each eagle in the subset using a global search strategy.
Step 7: Randomly select a subset of eagles to perform local search.
Step 8: Update the position of each eagle in the subset using a local search strategy.
Step 9:Evaluate the fitness of each eagle.
Step 10: If an eagle has higher fitness than the current best solution, update the current best solution.
Step 11: Return the current best solution.

3.2 Cat Swarm Optimization Algorithm (CSOA)

The Cat Swarm Optimization (CSO) Algorithm is a nature-inspired optimization algorithm that is based on the hunting behavior of cats. The algorithm was first introduced by Xin-She Yang in 2010 as a population-based metaheuristic optimization algorithm. In CSO, each cat represents a candidate solution to the optimization problem, and the population of cats is iteratively updated in order to find the optimal solution. The algorithm consists of the following steps:

Step 1. Initialization: A population of cats is randomly generated as the initial population.
Step 2. Fitness evaluation: The fitness of each cat is evaluated using an objective function that measures the quality of the solution.
Step 3. Update cat positions: Each cat updates its position based on the positions of other cats in the population. There are two main strategies for updating cat positions: Move according to its personal best position: Each cat remembers its own best position and moves towards it with a certain probability. Move towards the best position of other cats: Each cat also moves towards the global best position found by the entire population with a certain probability. The probabilities for each strategy can be adjusted based on the performance of the population in previous iterations.
Step 4. Abandonment and reproduction: Some cats may abandon the search and generate new solutions randomly, while others may reproduce and generate new solutions based on their current position and velocity.

Update the global best position: The best solution found by the entire population is updated if a cat finds a better solution. Termination: The algorithm terminates when a stopping criterion is met, such as a maximum number of iterations or when the population converges to a solution.

4 RESULT AND DISCUSSION

The BESOA aided semi-blind joint channel estimation, and data detection scheme was studied through simulation. The BER performance was measured for the frame length 50 and 100 with a MIMO system with $NT = 4$ and $NR = 4$. For SNR 15 dB, the BER is 10^{-3} with TFT OFDM with group pilots and BER is 10^{-2} with conventional CP-OFDM. With the swarm intelligent algorithm BESOA, the BER for SNR 15 dB is 10^{-6}.

In wireless communication channel estimation is very crucial. Computation time is also a very important factor especially in the case of TDD. Correctness of symbol detection and encoding very much rely on CSI. As our proposed methods minimize the error in channel estimation to a great extant with minimal computational complexity we hope that it will contribute to the sector. Getting optimal result with lesser iteration is the motivation of our future work. Tab. 1 shows the Simulation Parameters for BESOA method used in our techniques.

Table 1 Simulation parameters for BESOA method

Parameters	Specification
Modulation Technique	16 QAM
No of subcarrier	128
Channel	Rayleigh with AWGN noise
Number of transmitting antenna	4
Channel length	6
Pilots	Group pilot with $d = 0$
Random Number (0 - 1)	0.15
Acceleration coefficient c_1, c_2	2
Number of symbols	50, 100
Velocity (V_{max})	1
Γ (small factor)	0.1
Inertia weight	0

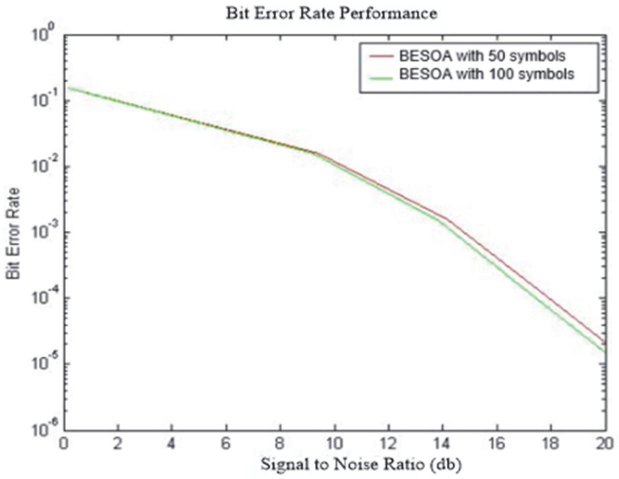

Figure 3 *BER* vs *SNR* performance using BESOA method

Tab. 2 shows the parameters used in this CSO method.

Table 2 Simulation Parameters for CSO method

CSO Parameters	CSO Specification
Subcarriers of OFDM (Nb)	128
Modulation Method	16 QAM
Channel	Rayleigh with AWGN noise
Number of pilots in a group	1, $d = 0$
Number of transmitters	4
Number of receivers	4
Number of symbols	50, 100
$I_0 = 1$, gamma	0.5

Fig. 4 shows the *BER* achieved for the CSOA methods and Fig. 5 shows the comparison of *BER* performance between BESOA and CSOA methods. Further, superposition of signals can cause distortion in signals. Also, the signals can be refracted in many objects and thus the fading or attenuation is the result. Also, the channel may be noisy. This channel effect has an issue when receiver tries to demodulate the received modulated signals sent from senders. The resultant signal often becomes inaccurate with respect to original signal sent. If the receiver somehow knows the properties of the propagation channel in advance, then the issue can be solved to a satisfactory extant.

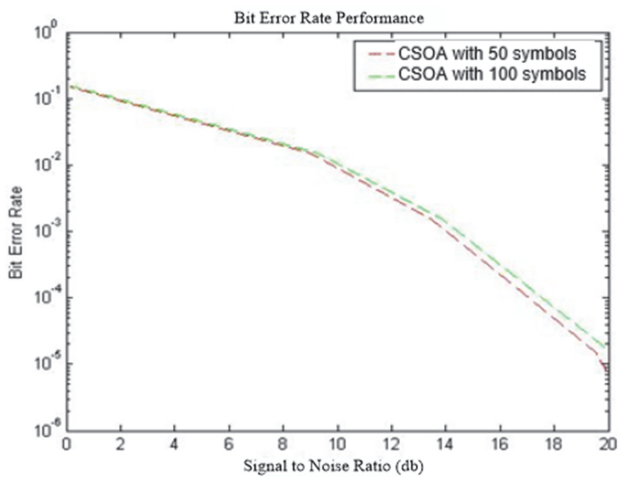

Figure 4 *BER* performance of CSOA

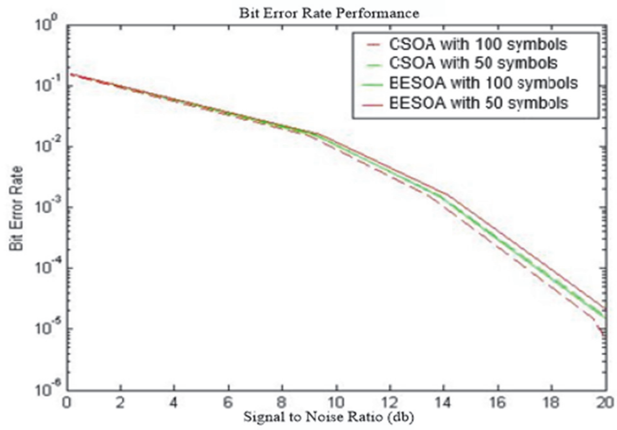

Figure 5 Comparison of *BER* performance using BESOA and CSOA method

It is evident from the graphs that the proposed CSOA method achieves lesser *BER* compared than BESOA technique.

5 CONCLUSION

The present study introduces a new approach for MIMO systems, which involves a semi-blind joint maximum likelihood (ML) channel estimation and data detection scheme. This approach decomposes the joint ML optimization over channel and data into an iterative two-level optimization loop. The Particle Swarm Optimization (BESOA) algorithm is employed for the purpose of estimating the channel coefficient that is not known a priori, as well as detecting the data that has been transmitted. The employed scheme is semi-blind, with a minimal pilot overhead utilized to aid in the initialization of the channel estimator based on Particle Swarm Optimization (BESOA). Meta-heuristic global search algorithms methods have been employed for optimizing an extensive range of challenging, huge scale methods. Meta-heuristics is an excellent method for resolving optimization problems. There are variations in channel estimation based on the type of training information included in the transmitted data. The pilot tones, headers or scattered pilot symbols placement in MIMO-OFDM can be categorized using meta-heuristics. CSOA algorithm has been considered as one of the meta-heuristic techniques developed for solving the optimization problems using the simulation of the behavior of the fireflies. In this work, FA-based joint time-frequency channel estimation in MIMO-OFDM is proposed. FA is on the basis of every CSOA attracting another CSOA based on its luminescent brightness. A CSOA with a lower intensity of luminescence is attracted to another CSOA with more intensity, and hence a search gap is discovered. Results show the achievement of the proposed CSOA method as less *BER* compared with BESOA technique. In future, investigate cooperative MIMO-OFDM schemes that leverage spatial diversity and user cooperation for channel estimation.

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