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Research Article

A Hybrid of Bacterial Foraging and Modified Cuckoo Search Optimization for Pilot Symbol Design in MIMO-OFDM Systems

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Abstract: Modern mobile telecommunication systems are using MIMO combined with OFDM, which is known as MIMO-OFDM systems, to provide robustness and higher spectrum efficiency. The major challenge in this scenario is to obtain an accurate channel estimation to detect information symbols, once the receiver must have the channel state information to equalize and process the received signal. Channel estimation is an essential task in MIMO-OFDM systems for coherent demodulation and data detection. Also designing pilot tones that affect the channel estimation performance is an important issue for these systems. For this reason, in this study we propose a Hybrid optimization algorithm (HBFOMCS) based on Bacterial Foraging Optimization (BFO) and Modified Cuckoo Search algorithm (MCS) to optimize placement of the pilot tones that are used for Least Square (LS) channel estimation in MIMO-OFDM systems. Simulation results show that designing pilot tones using the hybrid algorithm outperforms other considered placement strategies in terms of high system performance and low computational complexity.

Keywords: BFO algorithm, channel estimation, hybrid algorithm, LS channel estimation, MCS algorithm, MIMO-OFDM

INTRODUCTION

Wireless communication systems require high supporting data rate transmission and quality of service. Orthogonal Frequency Division Multiplexing (OFDM) is regarded as a promising solution for supporting these requirements. OFDM is a multicarrier modulation scheme that divides the available bandwidth into a number of orthogonal subcarriers that are modulated independently. High bit rate data transmission can, therefore, be provided by using bandwidth efficiently (Nee and Prasad, 2000). Additionally, multiple antenna architecture on the transmitter and receiver side, which is called the Multiple-Input Multiple-Output (MIMO) technique, is a suitable choice to improve the capacity of OFDM without additional power or bandwidth consumption (Paulraj *et al*., 2004). Due to the many advantages of MIMO-OFDM, it has been standardized for various digital communication systems such as Terrestrial Digital Audio Broadcasting (DAB-T), Terrestrial Digital Video Broadcasting (DVB-T), Wireless Local Area Networks (WLANs) and 4G wireless cellular systems.

MIMO-OFDM systems require the Channel State Information (CSI) for coherent demodulation and symbol detection. Channel state information can be obtained by pilot based channel estimation techniques. In these techniques, pilot tones are inserted into all subcarriers of OFDM symbols with a specific period or inserted into each OFDM (Coleri *et al*., 2002; Seyman and Taspinar, 2008, 2012a). Although these techniques provide better resistance to the fading channels, how to design the placement of pilot tones can affect the estimation performance significantly. So, the pilot tones design has been investigated by many researchers recently. In Minn and Al-Dhair (2008), Barhumi *et al*. (2003) and Wu *et al*. (2005), optimal design and placement of the pilot symbols based on minimizing Mean Square Error (MSE) of LS channel estimation have been derived. In Dong and Tong (2002), the optimization of these parameters based on minimizing Cramer Rao Bound of the channel has been presented. In Panah *et al*. (2009) the pilot tones location by considering the upper bounds on the Symbol Error Rate (SER) has been optimized. In Hu and Wang (2011), a new formulation based on Gerschgorin disc theorem for the placement problem of pilot tones has been presented

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for OFDM based cognitive radio systems. In Zhang *et al*. (2010), optimal pilot tone placement and its power allocation have been provided for non-contiguous OFDM systems. In Mavrokefalidis *et al*. (2010), optimum training design and placement has been studied for channel estimation in frequency selective, single relay forward cooperative system. In Kim *et al*. (2012), an optimal and a suboptimal pilot cluster sequence for OFDM system under rapidly time varying channel has been proposed. In Kang *et al*. (2011), the optimal pilot design criterion has been provided by minimizing the worst-case MSE of LS based channel estimation. Besides, nature inspired algorithms such as Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithm have been considered in channel estimation problem in MIMO-OFDM systems. In Xu *et al*. (2009), PSO based LS algorithm in MIMO-OFDM system has been proposed to decrease the effect of noise. In Seyman and Taspinar (2011), an optimal solution for designing pilot tones of LS channel estimation in MIMO-OFDM system using PSO algorithm has been investigated. In Seyman and Taspinar (2012b), DE algorithm has been proposed for optimizing not only the placement of pilot tones but also its power in MIMO-OFDM systems. In Seyman and Taspinar (2013), an optimal solution for designing pilot tones of LS channel estimation in MIMO-OFDM system using ABC algorithm has been investigated.

Nowadays, new algorithms are emerging by combining two or three algorithms called hybrid algorithms, which uses some combination of deterministic and randomness, or combines one algorithm with another so as to design more efficient algorithms. Genetic algorithm can be hybridized with many algorithms such as particle swarm optimization; more specifically, may involve the use of generic operators to modify some components of another algorithm. In Chia-Feng (2004), hybrid algorithm of GA and PSO was proposed for evaluating the performance of the design of recurrent neural and recurrent fuzzy network. In Dong *et al*. (2007) a novel hybrid approach consisting of a GA (Genetic Algorithm) and BFO (Bacterial Foraging) was proposed and the performance was illustrated for tuning a PID controller of AVR system. A hybrid optimization algorithm of PSO and Cuckoo search was proposed (Fan *et al*., 2011) to increase the search area of PSO using CS. A hybrid cuckoo search and genetic algorithm was proposed (Kanagaraj *et al*., 2013) to solve the nonlinear mixed-integer reliability optimization problems.

The Bacterial Foraging Optimization (BFO) algorithm is a modern evolutionary computation technique, which is predominately used to find solutions for real-world problems. Recently many literatures belong to various domains have proven the efficiency and low complexity of BFO as follows: optimization of the efficient frontier (mixed quadratic and integer programming problem) (Kanagaraj *et al*., 2013), portfolio optimization (Yucheng and Hsiu-Tzu, 2013) Cell Formation (CF) problem of manufacturing system (Hossein and Tang, 2013), to optimize the integral gains of the Load-frequency Controller under different transactions in the competitive electricity market (Chidambaram and Paramasivam, 2013) and optimal load shedding in power system (Afandie *et al*., 2013). In Afandie *et al*. (2013), a simple scheme was designed for adapting the chemotactic step size of each field to accelerate the convergence speed of the group of bacteria near the tolerance. In Manjith and Suganthi (2013a), Partial Transmit Sequences (PTS) algorithm based on the BFO algorithm for peak-to-average power ratio reduction was proposed to reduce the computational complexity of the PTS method in MIMO-OFDM system.

A new robust optimization algorithm called Modified Cuckoo Search (MCS), which can be regarded as a modification of the recently developed cuckoo search, had received lot of attention in recent years. Recently many literatures belong to various domains have proven the efficiency of MCS and review study of Pinar and Erkan (2013) compares cuckoo search with ABC, DE and PSO algorithms and states that the performances of the CK and PSO algorithms are statistically closer to the performance of the DE algorithm than the ABC algorithm. The CK and DE algorithms supply more robust and precise results than the PSO and ABC algorithms. In Walton *et al*. (2013), MCS is applied to perform the optimization of unstructured meshes and also applied for coordinated stabilizer tuning to New England test system and achieved better performance than the GA (Peres *et al*., 2013). In Manjith and Suganthi (2013b), Partial Transmit Sequences (PTS) algorithm based on MCS algorithm for peak-to-average power ratio reduction was proposed to reduce the computational complexity of the PTS method in MIMO-OFDM system.

The aim of this study is to propose an optimization for the location of pilot tones affecting the performance of the LS channel estimation technique in MIMO-OFDM systems by using a hybrid BFOMCS optimizer. Since BFO and MCS algorithm gives best optimization solution for PAPR reduction the same can be utilized for optimizing the placement of pilot tones for channel estimation. Better optimization solution can be obtained by hybridizing BFO and MCS algorithms.

The fitness function of MSE of LS estimation algorithm has high computational complexity due to the matrix inversion. The hybrid of BFO and MCS provides a better optimization solution for the fitness function of MSE of LS algorithm directly which involves high computational complexity. Compared with PSO (Seyman and Taspinar, 2011), ABC (Seyman and Taspinar, 2013), DE (Seyman and Taspinar, 2012b) and other classical pilot tones placement strategies, HBFOMCS assisted pilot tones design shows a better performance in LS estimation for MIMO-OFDM systems.

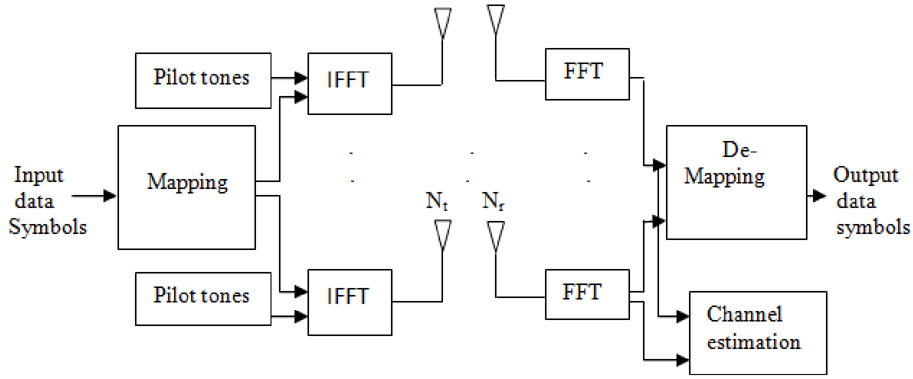

Fig. 1: Block diagram of MIMO-OFDM system

METHODOLOGY

MIMO-OFDM system model: In a traditional wireless communication system, provided that the bandwidth is constant, there is no possibility of increasing the sending rate of information. In this kind of situation, only diversity methods can be used to improve the quality of revealing. In designing communication systems, bandwidth, information sending rate and software-hardware complexities are the important parameters. To expand the new generation of communication systems, methods such as MIMO, OFDM and integrating them together as MIMO-OFDM, are suggested.

The high intrinsic resistance of OFDM against the ISI event and its suitable function against fading destructive event, besides the high rate of information sending of MIMO, creates a very efficient complex in accession toward the fourth generation of wireless communication's demands. Like OFDM systems, the MIMO-OFDM systems have a great deal of sensitivity toward synchronization errors. Again, according to the increase in number of unknowns, estimating the channel in these systems are more complex than estimating channel in one antenna systems (Foschini and Gans, 1998).

A block diagram of a MIMO-OFDM system with N_t transmitter and N_r receiver antenna and N subcarrier, is shown in Fig. 1. The binary data symbols are first mapped according to the modulation type. After pilot tones are inserted, N point Inverse Fast Fourier Transform (IFFT) converts the symbols into the time domain. Following the IFFT block at each transmitter antenna Cyclic Prefix (CP) is inserted to avoid Inter Symbol Interference (ISI). Then the symbols consisting of data and pilot tones are transmitted from i^{th} transmitter antenna. After removing CP and taking the DFT at the j^{th} receiver antenna, the received N×1 signal tones vector $Y_j(n)$ can be written as:

$$Y_j(n) = \sum_{i=1}^{N_t} X_i{}^{diag}(n) F h_{i,j} + W_j(n) \quad (1)$$

$$i = 1,2 \ldots\ldots N_r \;\; j = 1,2 \ldots\ldots N_t$$

where $h_{i,j}$ is L length L×1 channel impulse response vector of belonging to i^{th} transmitter antenna to j^{th} receiver antenna, $W_j(n)$ is the additive white Gaussian noise. $X_i(n)$ consist of N×1 data vector = $S_i(n)$ and N×1 pilot tone vector = $P_i(n)$ at time index n:

$$\mathrm{X}_i(n) = \mathrm{S}_i(n) + \mathrm{P}_i(n) \quad (2)$$

F is $(1/\sqrt{N})$ times the $N \times N$ unitary DFT matrix:

$$F = \begin{bmatrix} 1 & 1 & 1 \\ 1 & e^{-\frac{j2\pi}{N}} & e^{-\frac{j2\pi(N-1)}{N}} \\ \ldots & \ldots & \ldots \\ 1 & e^{-\frac{j2\pi(N-1)}{N}} & e^{-\frac{j2\pi(N-1)(N-1)}{N}} \end{bmatrix} \quad (3)$$

By assuming training over g consecutive OFDM symbols, we can write Eq. (1) as:

$$Y_j(n) = \sum_{i=0}^{N_t-1} S_i{}^{diag}(n) F h_{i,j} + \sum_{i=0}^{N_t-1} P_i{}^{diag}(n) F h_{i,j} + W_j(n) \quad (4)$$

If we write Eq. (4) in simplified form:

$$Y_j = G h_j + A h_h + W_j \quad (5)$$

where G = $[P_1^{diag} F, \ldots, P_{N_t}^{diag} F]$ is N×$N_t L$ sized matrix, $A = [S_1^{diag} F, \ldots, S_{N_t}^{diag} F]$ is a N×N_t L. N_t L length channel impulse response of each antenna is given as:

$$h_j = [h_j, 1^T \ldots, h_j, N_t{}^T]^T \quad (6)$$

where $(.)^T$ is transpose operation.

CHANNEL ESTIMATION

Basically, methods of channel estimation can be classified according to four dimensions. From the view of estimation theory, there are Least Square (LS) Estimation and Minimum Mean Square Error (MMSE) estimation. According to the processing domain, estimation can be done in time domain and frequency domain. Due to the different pilot symbol arrangements, there are estimator with block type pilot (training based) and estimator with comb type pilot (pilot symbol aided modulation). With different estimation iteration, there are iterative methods and direct methods.

Based on those assumptions such as perfect synchronization and block fading, we end up with a compact and simple signal model for both the single antenna OFDM and MIMO-OFDM systems. In training based channel estimation algorithms, training symbols or pilot tones that are known to the receiver, are multiplexed along with the data stream for channel estimation. The idea behind these methods is to exploit knowledge of transmitted pilot symbols at the receiver to estimate the channel. For a block fading channel, where the channel is constant over a few OFDM symbols, the pilots are transmitted on all subcarriers in periodic intervals of OFDM blocks. This type of pilot arrangement is called the block type arrangement. For a fast fading channel, where the channel changes between adjacent OFDM symbols, the pilots are transmitted at all times but with an even spacing on the subcarriers, representing a comb type pilot placement. The channel estimates from the pilot subcarriers are interpolated to estimate the channel at the data subcarriers.

LS channel estimation: By using the LS channel estimation algorithm, each of the channel impulse response h_j can be estimated as:

$$\widehat{h_j} = G^t Y_j = h_j + (G^H G)^{-1} G^H W_j = h_j + G^t W_j \tag{7}$$

We assume that pilot tones are designed as $gN \times LN_t$ sized matrix, G is full column rank LN_t which requires $gN \geq LN_t$. $(.)^t$ and $(.)^H$ are matrix pseudo inverse and hermitian matrix, respectively. MSE of LS estimation is given by:

$$MSE = \frac{1}{LN_t} \varepsilon\left\{\left[\!\left[\widehat{h_j} - h_j\right]\!\right]^2\right\} = \frac{1}{LN_t} \varepsilon\left\{\left[\!\left[G^t W_j\right]\!\right]^2\right\} \tag{8}$$

$$= \frac{1}{LN_t} tr\left\{G^t \, \varepsilon\left\{W_j {W_j}^H\right\} G^{t\,H}\right\} \tag{9}$$

where, tr (.) is trace operator and ε(.) is expectation. If we assume $\varepsilon\left\{W_j {W_j}^H\right\} = \sigma^2 I_m$ for zero mean white Gaussian noise where σ^2 is noise variance, the MSE can be written as:

$$MSE = \frac{1}{LN_t} \{(GG^H)^{-1}\} \tag{10}$$

The minimum MSE can be achieved if $GG^H = PI_{LN_t}$ where P is fixed power dedicated for pilot tone. Thus the minimum MSE can be given by Barhumi *et al*. (2003):

$$MSE = \frac{\sigma^2}{P} \tag{11}$$

HYBRID BFOMCS ALGORITHM FOR PLACEMENT OF PILOT TONES

In order to optimize pilot tones, MSE function Eq. (11) can be used as fitness function for the optimization algorithms. However, if this equation is used as the fitness function directly, computational complexity will increase because of matrix inversion of Eq. (11). Inspite of the increase in computational complexity of the MSE equation, the Hybrid of BFO and MCS algorithm (HBFOMCS) is applied directly by considering this MSE equation as the fitness function proving the proficiency of the proposed hybrid algorithm:

$$MSE = \frac{\sigma^2}{P} \tag{12}$$

In order to get the OFDM signals with the minimum MSE, a suboptimal combination method based on the hybrid of Bacterial Foraging (BFO) and Modified Cuckoo Search (MCS) algorithm is proposed to solve the optimization of placement of pilot tones in LS channel estimation method. The hybrid algorithm with lower complexity can get better MSE and BER performance. The minimum MSE for LS channel estimation method is relative to the problem: Minimize $MSE = \frac{\sigma^2}{P}$ subject to the number of possibilities of placement of pilot tones.

Hybrid of BFO and MCS (HBFOMCS): The initial motivation of developing hybrid HBFOMCS approach is to combine the advantages of both MCS and BFO. To find an optimal solution to an optimization problem is often a very challenging task, depending on the choice and the correct use of optimization technique. HBFOMCS algorithm is proposed to achieve the better search ability with less computational complexity. In BFO, the concept of swim is obliged to increase the search area, since it terminates only when the best solution is obtained. However, the optimized best solutions may be eliminated in the elimination dispersal step of BFO. In MCS, information exchange between every solution is maintained to achieve the high convergence rate while their search area is limited by Lévy flight. At the end, we believe in the hybridization of BFO and MCS to overcome their disadvantages with advantages of each other. Hence, the swim step is utilized once initial generation is produced. Therefore, search area of the problem is increased and accordingly best solutions can be optimized by the further steps. The reproduction and elimination dispersal operation of BFO is replaced with the searching ability of MCS using Lévy flight. This can provide us to prevent the elimination of best solution from the population; therefore, every generation is forced to search best solution by swim step.

The Hybrid optimization algorithm, HBFOMCS consists of three major operators:

- Population or initialization
- Swim and tumble
- Reproduction with Lévy flight

This hybrid optimization algorithm utilizes the capable properties of MCS in BFO algorithm to achieve the better search ability with less computational complexity. The reproduction and elimination dispersal operation of BFO is replaced with the searching ability of MCS using Lévy flight. The Hybrid optimization algorithm, HBFOMCS consists of three major operators.

Initialization: In HBFOMCS, MCS work with the same population. Initially, N individuals constituting the population should be randomly generated as in MCS. These individuals may be regarded as nests in terms of MCS, or as positions of bacterium in terms of BFO. In addition, the optimization parameters, such as maximum tumble, maximum swim, discover probability and maximum Lévy step size should be initialized. After initialization, new nests on the next generation are created by swim, tumble and reproduction operations.

Swim and tumble: In each generation, after the fitness values of all the nests in the same population are calculated, then the fitness values of N nests are calculated to bring out the individuals (position or nest) with best solutions (food or egg). In case, if maximum swim does not generate best individuals then tumble procedure is performed to change the direction of bacteria or cuckoo. These individuals are regarded as elites. Instead of performing unlimited tumble steps as in BFO, HBFOMCS confines the maximum number of tumble steps as initialized. This enhancement procedure tries to imitate the maturing phenomenon in nature, where individuals will become more appropriate to the environment after attaining data from the society. Furthermore, by using this enhanced procedure in tumble step, the never-ending situation can be avoided while an ultimate individual has been generated in swim step.

Reproduction with lévy flight: To produce well performing individuals, in the reproduction operation nests are reproduced by enhanced reproduction. To reproduce the nest, the Lévy flight of MCS is used and the discover probability is applied to select the individuals. Thus, the top nests are reproduced after their fitness values are compared with the new individuals produced by Lévy flight.

The adopted reproduction may be regarded as a kind of elite reproduction and is used to increase the searching ability. As in nature, individuals selected have guaranteed ability to search new individuals will achieve better fitness than those by usual reproduction as in BFO. After top nests are reproduced, bottom nests or individuals are replaced by Lévy flight without comparing the fitness function. From the perspective of BFO, where bottom individuals are replaced by applying elimination dispersal probability (discover probability).

$(N*G_n)$ is the measure of computation complexity or the number of searches for the proposed HBFOMCS-PTS algorithm, where N is the initial number of nests considered for optimization and $G_n = N-1$ is the number of generations considered for computation.

The mathematical model of hybrid algorithm is explained as follows.

HBFOMCS algorithm:

A←Max Lévy Step Size
MaxTumble←Allowed tumble steps
MaxSwim←Allowed swim steps
P_d←Discover Probability
$P_s = 1-P_d$ ←Select Probability
S←Split Position
Initialize a population of n nests x_i ($i = 1, 2, ..., n$)
for all $x_i$do
  Calculate fitness $F_i = f(x_i)$
end for
Generation number G←1
while $G \le G_{max}$do
  G←G + 1
for all x_i do
$F_{temp} = F_i$
p = i+1
tumble = 0
while tumble≤MaxTumble
  swim = 0
while swim<MaxSwim
  p = p+swim
if $F_p \le F_{temp}$
$F_{temp} = F_p$
  swim + = 1
else
break;
end if
end while

p = random position among nest
tumble+ = 1
end while
 $F_i = F_{temp}$
$x_i = x_{temp}$
end for
 Sort nests by order of f (x_i)
 S = P_s * n
for i = S+1: n do
 Current position x_i
 Calculate Max Lévy Step Size A
 Perform Lévy flight from x_i to generate new egg x_k
$x_i \leftarrow x_k$
 $F_i \leftarrow f(x_i)$
end for
for i = 1: S do
Current position x_i
Pick another nest from the top nests at random x_j
Calculate Max Lévy Step Size A
Perform Lévy flight from x_i to generate new egg x_k
$F_k = f(x_k)$
Choose a random nest l from all nests
if ($F_k > F_l$) do
$x_l \leftarrow x_k$
$F_l \leftarrow F_k$
end if
end for
end while

As we can see from the Eq. (3), *h*1 and *h*2 channel impulse responses must be estimated for 2×2 MIMO-OFDM systems. In order to estimate each response, the LS estimation algorithm is used individually and how to locate the pilot tones is an important issue for LS algorithm. So, the location of the pilot tones which are sent from the each transmitter antenna is found using the hybrid algorithm.

In order to optimize the positions of pilot tones, the populations called pilot positions are first initialized at random values between 0 and 63 and 0 and 127. Possible combinations of pilot positions are tested using the fitness function σ^2/P. In order to get the best positions of the pilots, their locations are improved by the steps of initialization, swim and tumble and reproduction with Levy flight as mentioned. The process is repeated until the termination criteria are reached, which was determined as a maximum of 100 iterations in our simulations. At the end of the iterations, the best locations were chosen.

SIMULATION RESULTS

To demonstrate the performance of the proposed pilot tones design method over random and orthogonal pilot tones design, the simulations are carried out for a 2×2 MIMO-OFDM system whose parameters are given in Table 1 and 2. The simulations are run for f_d = 5 Hz and f_d = 40 Hz Doppler shifts. Control

Table 1: MIMO-OFDM simulation parameters for 128 subcarriers

Parameter	Value
FFT size	128
Number of subcarrier	128
Cyclic prefix size	FFT/4 = 32
Number of pilot tones	16
Modulation type	QPSK
OFDM symbol duration (τs)	1.13 ms

Table 2: MIMO-OFDM simulation parameters for 64 subcarriers

Parameter	Value
FFT size	64
Number of subcarrier	64
Cyclic prefix size	FFT/4 = 16
Number of pilot tones	8
Modulation type	QPSK
OFDM symbol duration (τs)	565 µs

Table 3: Simulation parameters for HBFOMCS

Simulation parameters	128 subcarrier	64 subcarrier
Initial population (N)	40	20
No. of Generations (G)	50	50
Max swim (N_s)	3	3
Max tumble(N_t)	2	2
Discover Probability (P_D)	0.4	0.4

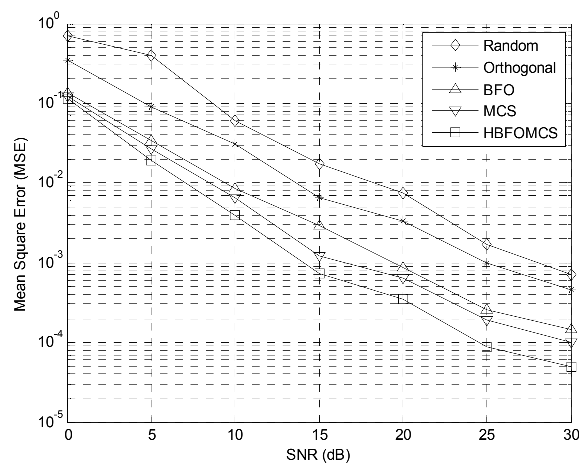

Fig. 2: MSE versus SNR for various pilot symbol with 128 subcarriers (f_d = 5 Hz)

parameter values of BFO, MCS and hybrid algorithm that are used for optimizing pilot tones are given in Table 3. In simulations, we evaluate the performance of various pilot tones:

- Randomly placed pilot tones
- Equispaced orthogonal pilot tones
- BFO optimized pilot tones
- MCS optimized pilot tones
- HBFOMCS optimized pilot tones

In Fig. 2 and 3, Mean Square Error (MSE) versus SNR (dB) and Bit Error Rate (BER) versus SNR (dB) of different pilot tones for 128 subcarriers over channels with Doppler frequency shift f_d = 5 Hz are shown, respectively. In Fig. 2, the performances of pilot

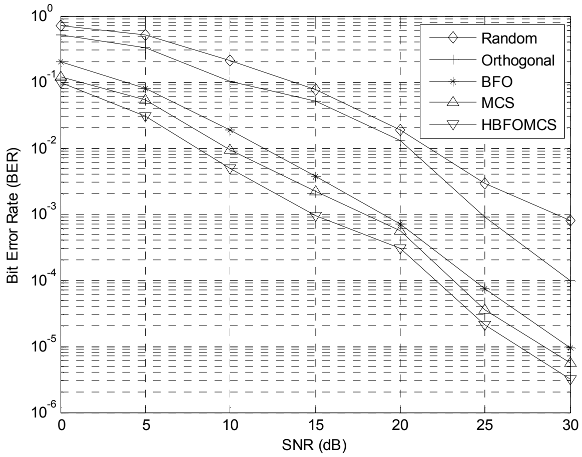

Fig. 3: BER versus SNR for various pilot tones with 128 subcarriers (f_d = 5 Hz)

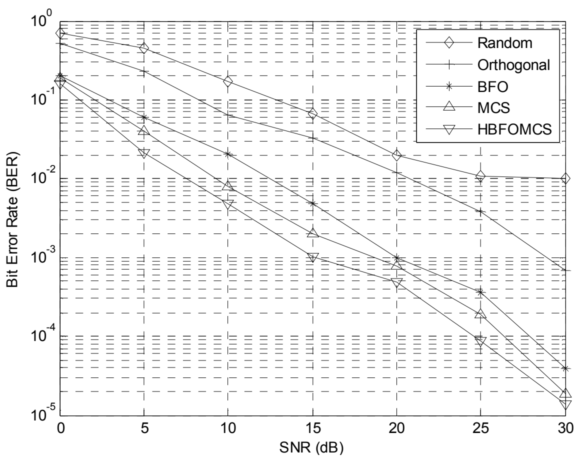

Fig. 4: BER versus SNR for various pilot tones with 128 subcarriers (f_d = 40 Hz)

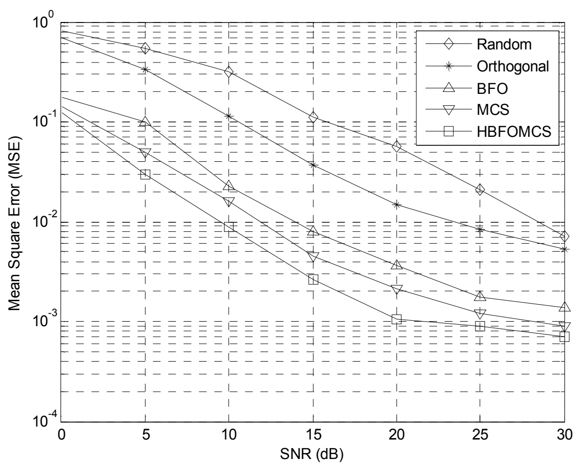

Fig. 5: MSE versus SNR for various pilot symbol with 64 subcarriers (f_d = 5 Hz)

tones design are measured by the Mean Square Error (MSE) for Doppler shift f_d = 5 Hz. The proposed technique gives improved MSE values compared to other placement techniques. From the Fig. 2, it is observed that the random placement requires 23 dB of SNR, orthogonal placement requires 18 dB of SNR, BFO based placement requires 16 dB of SNR, MCS based placement requires 15 dB of SNR, whereas HBFOMCS based placement requires 13 dB of SNR to have MSE = 10^{-3}. At 30 dB SNR value, while the MSE difference between orthogonal and HBFOMCS based placement is 10^{-1}, this difference between our proposal and random placement is about 10^{-2}. Also this technique results in 2 and 4 dB degraded performance near 10^{-3} MSE in comparison with MCS and BFO based pilot tones design and 6, 8 and 8 dB, respectively degraded performance near 10^{-3} MSE in comparison with ABC (Seyman and Taspinar, 2013), PSO (Seyman and Taspinar, 2011) and DE (Seyman and Taspinar, 2012b) based pilot tones design.

Figure 3 illustrates the Bit Error Rate (BER) performance of the pilot tones design for Doppler shift f_d = 5 Hz. As it can be seen from Fig. 3, HBFOMCS based pilot tones design performs better than the other pilot tones design techniques not only at high SNR values but also at low SNR values. This performance advantage increases further in increasing SNR values. HBFOMCS based placement technique shows about 7 dB advantages relative to the orthogonal placement at the BER of 10^{-2}. This advantage over BFO placement is about 2 dB at the BER of 10^{-2}. It also performs better than MCS based placement technique of about 1 dB at the BER of 10^{-2}. At 10^{-3} BER we achieved about 1 and 3 dB SNR gain over ABC (Seyman and Taspinar, 2013) and PSO (Seyman and Taspinar, 2011) assisted pilot tones strategy and also 1 dB SNR gain over DE (Seyman and Taspinar, 2012b) assisted pilot tones strategy.

Besides, the BER values of the pilot tones placement strategies for f_d = 40 Hz Doppler shift are shown in Fig. 4 in order to evaluate the performances over the channel with increased Doppler shift. As it can be seen from Fig. 4, optimizing pilot tones using the HBFOMCS algorithm makes the system robust against the Doppler shifts. When we consider Fig. 5, there is 6 dB SNR difference between HBFOMCS based optimum placement and orthogonal placement of pilot tones at BER of 10^{-2}. Furthermore to have BER = 10^{-3}, PSO (Seyman and Taspinar, 2011) based placement needs 24 dB, DE (Seyman and Taspinar, 2012a) based placement needs 23 dB, ABC (Seyman and Taspinar, 2013) based placement needs 22 dB, BFO placement needs 20 dB, MCS placement needs 19 dB and HBFOMCS placement needs 18 dB.

The MSE performances of the placement schemes are also investigated in Fig. 6. From the Fig. 6 we can see that to reach MSE = 10^{-3}, the random placement requires 23 dB of SNR, orthogonal placement requires 18 dB of SNR, BFO requires 15 dB of SNR, MCS requires 14 dB of SNR but HBFOMCS requires 13 dB of SNR. The MSE difference between HBFOMCS,

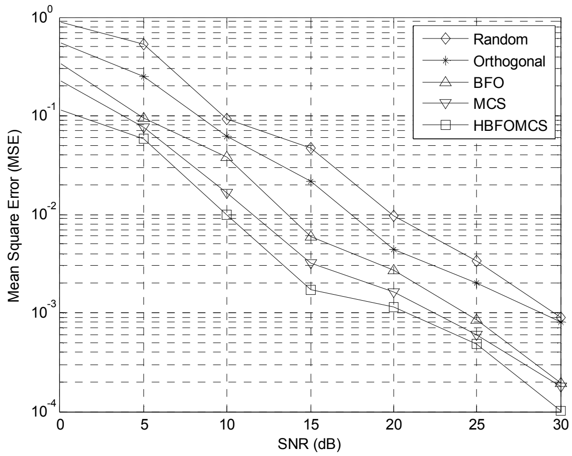

Fig. 6: MSE versus SNR for various pilot symbol with 128 subcarriers (f_d = 40 Hz)

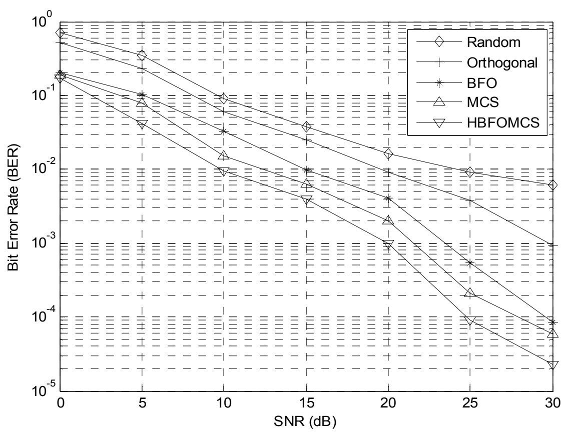

Fig. 7: BER versus SNR for various pilot tones with 64 subcarriers (f_d = 5 Hz)

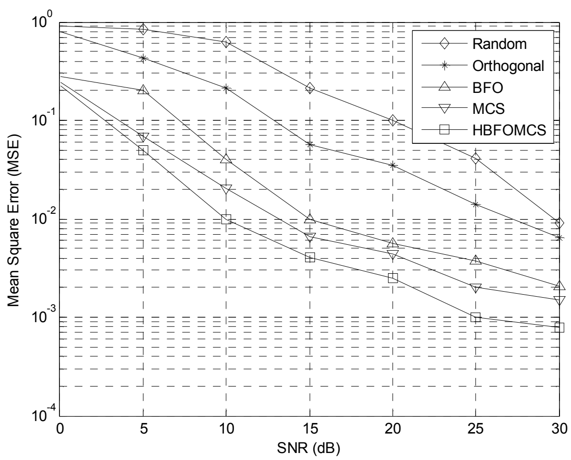

Fig. 8: MSE versus SNR for various pilot symbols with 64 subcarrier (f_d = 40 Hz)

ABC (Seyman and Taspinar, 2013), DE (Seyman and Taspinar, 2012a) and PSO (Seyman and Taspinar, 2011) placement is more than 10^{-1} at 25 dB SNR value.

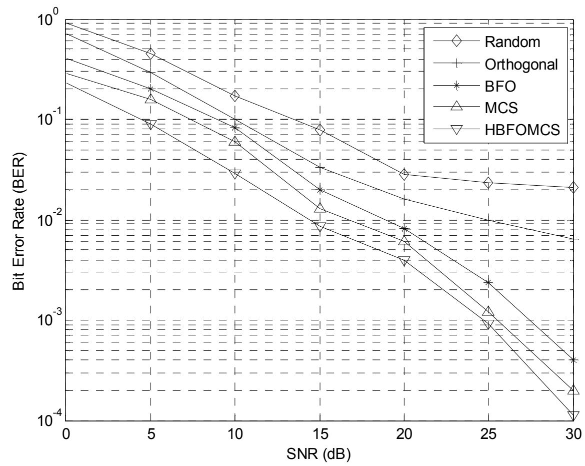

Fig. 9: BER versus SNR for various pilot tones with 64 subcarriers (f_d = 40 Hz)

According to these figures, when Doppler shifts increase channel estimation errors also increase. However, optimizing pilot tones makes the system robust. Results obtained show that our proposal enhances the system performance against the Doppler shifts significantly.

Also to show the effect of number of subcarrier on system performance, BER and MS of the systems which have 64 subcarriers are simulated in Fig. 5 and 7 to 9. According to these figures, system performance is decreased with the reduction of the subcarrier number. Because a greater number of subcarriers can offer a better protection against multipath delay spread. For instance, when we consider to Fig. 4 and 9, at 20 dB SNR value the BER difference of optimized pilot tones is approximately 10^{-1}.

In addition to the performance advantages of HBFOMCS which can be seen from above figures, HBFOMCS also avoids exhaustive searches to optimize pilot tones location. For each antenna, exhaustive search of pilot position as in orthogonal pilot's needs $C^{16}_{128} \approx 2.26041\times10^{28}$ searches for 128 subcarriers and 16 pilot tones; and $C^{8}_{64} \approx 4.426\times10^{6}$ searches for 64 subcarrier and 8 pilot tones; conversely the number of search in HBFOMCS is just $100\times20 = 2\times10^{3}$ for 100 iteration and 20 particle sizes.

As it can be seen from the above complexity analysis, optimizing location of pilot tones based on HBFOMCS has computational complexity advantage over orthogonal placement of pilot tones. The complexity of orthogonal placement of pilot tones becomes quite high when the number of subcarrier is increased. Because increasing number of subcarrier also increase the number of pilot tones in MIMO-OFDM systems.

CONCLUSION

In this study, we have proposed an efficient pilot tones design method based on the hybrid BFOMCS algorithm to optimize the placement of pilot tones that are used in the LS channel estimation in MIMO-OFDM systems. According to the simulation results, our proposal performs better than random, orthogonal, BFO, MCS, PSO and ABC based placement strategies for various Doppler shifts. Furthermore, this method has the computational complexity advantage over the orthogonal placement of pilot tones. Hence it is concluded that the hybrid BFOMCS algorithm is an alternative solution to achieve both high-performance efficiency and low-computational complexity in designing pilot tones.

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