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Deterministic Pilot Pattern Placement Optimization for OFDM Sparse Channel Estimation

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ABSTRACT Compressed sensing (CS) technologies have been widely adopted to pilot-assisted orthogonal frequency division multiplexing (OFDM) sparse channel estimation. However, only few works have focused on the location optimization of the pilot pattern. This paper investigates the pilot location optimization for the measurement matrix construction based on the minimum mutual coherence (MC) rule. We consider the design of the deterministic OFDM pilot pattern for solving a combinatorial optimization problem. The proposed approach utilizes the advantages of the Q-bit to update the location of the OFDM pilot pattern. The obtained results show that the proposed approach can form measurement matrix with a smaller MC and the estimated performance can be essentially improved compared with the standard genetic algorithms or random search method.

INDEX TERMS Channel estimation, genetic algorithm, Q-bit, pilot pattern, mutual coherence.

I. INTRODUCTION

The well-konwn orthogonal frequency division multiplexing (OFDM) theory provides a multicarrier modulation mechanism, which divides the valid spectrum into numerous parallel orthogonal narrow-band sub-channels [1]. It can effectively eliminate the multipath effect in wireless propagation and reduce the receiver complexity and the power consumption. However, the propagation paths between the receiver and the transmitter are complex, which causes distortion in the phase, frequency and amplitude of the received signal. The accuracy of channel estimation is an important factor that affects the demodulation and channel equalization [2]–[6]. Therefore, channel estimation is a key part of the OFDM wireless systems.

Due to the innate multi-path sparse structure in the wireless channels, the sampled taps of the channel impulse response (CIR) are usually close or equal to zero indicating that the CIR is a sparse signal. Therefore, numerous sparse reconstruction algorithms have been used for OFDM sparse channel estimate [7]–[13]. Compared to the standard estimation method of least squares (LS), the sparse channel estimation effectively reduces pilot overhead and increases the spectrum utilization [14], [15].

For further enhancing the channel estimation accuracy, an effective mechanism is to optimize the pilot pattern. Although the LS method uses equispaced pilot placement in the traditional channel estimation, the random location of the pilot can achieve good estimation performance in sparse multipath channel. Reference [16] introduces the optimized pilot pattern based on random search method, in which the pattern with the smallest mutual coherence (MC) has been chosen as the optimum pilot. The optimization approach can generate suboptimal pilot pattern in the limited time. However, the choice of the optimal solution depends on the range of the set. Two optimization methods, based on cross-entropy optimization [17], [18] and discrete random approximation [19], have been used to update the location of the pilot pattern. However, these two methods are essentially random methods and the convergence cannot be guaranteed. Therefore, it is necessary to design the location placement for the deterministic pilot pattern to guarantee the estimation accuracy in an OFDM system.

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A. RELATED WORK

The location of the pilot pattern plays a critical role for enhancing the accuracy of the channel estimation. In [16]–[19], the optimization of the OFDM pilot pattern has been summarized as a combinatorial problem. To overcome the drawbacks of the random search method, various methods have been introduced for solving the problem within a limited time and generating the optimum solution. Pilot pattern optimal methods that use genetic algorithms (GA) to search the optimal solution have been presented [20]–[22]. Furthermore, a few evolutionary schemes have been employed for solving the optimization problem to generat sub-optimal pilot pattern. These algorithms include the estimation of distribution algorithm (EDA) [23], particle swarm optimization [24], [25], bat-inspired algorithm (BA) [26], and whale optimization algorithm (WOA) [27]. However, due to the influence of parameter setting, the convergence accuracy and the time of the above-mentioned methods cannot be ensured. Therefore, this paper investigates a method using modified quantum-genetic algorithm (MQGA) to attain the deterministic location for the OFDM pilot pattern.

Quantum genetic-algorithm (QGA) in [28] is an innovative intelligent evolutionary algorithm that can combine evolutionary algorithm and quantum computing. In QGA, Q-bit is the minimum element of information representation that is used to encode individuals in a population. Compared with numeric and binary representations, individuals represented with Q-bits have better diversity. Due to the diversity and the global convergence of the QGA, it has been adopted as an effective method to solve combinatorial problem in recent years [29]–[32].

B. OUR CONTRIBUTION

Although the QGA is an effective scheme to solve the optimization problem, only few works have focused on the deterministic location design for the OFDM pilot pattern using QGA. Therefore, in this paper, the MQGA-based scheme is considered to generate the deterministic pilot pattern for obtaining better estimation performance. In the optimization process, a combinatorial problem is used to describe the pilot pattern design by the MC minimization of the measurement matrix. Then, the MQGA method is utilized for solving the optimization problem to form the optimum pilot. The results indicate that our proposed MQGA-based algorithm can design measurement matrix with lower MC and enhance the estimation accuracy by comparing with the standard genetic algorithms and the random method.

The main contributions of this work are as follows:

1) The MQGA is proposed to enhance the QGA performance by adjusting the update strategy of the rotation angle in the iteration procedure. The angle is defined as a variable related to the population generation to dynamically adjust the search space.
2) An MQGA-based optimization scheme is presented that combines the quantum computing and GA to search the optimum deterministic pilot pattern using the minimum MC of the measurement matrix.
3) In order to evaluate the validity of the proposed scheme, simulations are conducted by comparing its performance with the equispaced, random search, the GA, the modified adaptive genetic algorithm (MAGA), and the conventional QGA.

The remainder of the paper is organized as follows. The channel estimation model of the OFDM frequency domain is briefly described and the location optimization of the pilot pattern is formulized as the optimization problem in Section II. We discuss the innovative contribution of this work in Section III. In this part, the MQGA is applied for solving the combinatorial problem to generate deterministic pilot pattern. In Section IV, the effectiveness of our approach is verified by MATLAB simulation. The conclusions of our work are summarized in Section V.

II. CHANNEL ESTIMATION MODEL AND PROBLEM FORMULATION

A. CHANNEL ESTIMATION MODEL

The traditional pilot-assisted channel estimation employs LS algorithm in OFDM systems. However, these methods require that the pilot patterns are equispaced. Wireless channel is a multi-path sparse structure [33]–[35], which means that few only coefficients of the CIR are non-zero. Therefore, compressed sensing (CS) technology shows that the CIR sparse vector can be precisely reconstructed with small amounts of measurements [36]–[38], which reduces the pilot overhead and increases the spectrum utilization.

Suppose the transmitted OFDM symbol with K subcarriers, where the pilot subcarriers are L. The location allocation in the pilot subcarriers depends on the pilot pattern $\Psi = (\Psi_1, \Psi_2, \cdots, \Psi_L)\,(1 \leq \Psi_1 < \cdots < \Psi_L \leq K)$. At the receiver, the pilot symbols are represented as

$$\mathbf{R} = \mathbf{SH} + \mathbf{Z} = \mathbf{SWh} + \mathbf{Z}, \tag{1}$$

where $\mathbf{R}$ is the received $L \times 1$ pilot symbols and $\mathbf{S} = diag\left[\mathbf{S}(\Psi_1), \mathbf{S}(\Psi_2), \cdots, \mathbf{S}(\Psi_L)\right]$ is the transmitted pilot matrix. $\mathbf{H} = \left[\mathbf{H}(\Psi_1), \mathbf{H}(\Psi_2), \cdots, \mathbf{H}(\Psi_L)\right]$ represents the $L \times 1$ channel frequency response (CFR). $\mathbf{h}$ corresponds to the $K \times 1$ sparse CIR vector between the receiver and transmitter. $\mathbf{W}$ denotes the $L \times K$ sub-matrix formed by selecting the index $(\Psi_1, \Psi_2, \cdots, \Psi_L)$ from the $K \times K$ DFT matrix. $\mathbf{Z}$ stands for the received $L \times 1$ additive white Gaussian noise term.

We redefine the matrix product in (1)

$$\mathbf{D} \triangleq \mathbf{SW} = \begin{bmatrix} \mathbf{S}(\Psi_1)w^{\Psi_1 1} & \cdots & \mathbf{S}(\Psi_1)w^{\Psi_1 K} \\ \vdots & \ddots & \vdots \\ \mathbf{S}(\Psi_L)w^{\Psi_L 1} & \cdots & \mathbf{S}(\Psi_L)w^{\Psi_L K} \end{bmatrix}, \tag{2}$$

where $w = e^{-j2\pi/K}$. Equation (1) can be rewritten as

$$\mathbf{R} = \mathbf{Dh} + \mathbf{Z}. \tag{3}$$

The matrix $\mathbf{D}$ in (3) is the measurement matrix, which is critical to improve the sparse signal vector recovery probability. Clearly, the received pilot signals **R** and the measurement matrix **D** are given to channel estimation. In the procedure of reconstructing the sparse vector **h**, the pilot location determines the structure of the **D** that directly infiuences the precision of sparse reconstruction algorithm. If the pilot location is randomly placed, the measurement matrix **D** generates random structure, which satisfies the well-known restricted isometry-property (RIP) to promote sparse signal vector reconstruction [39]. However, the random OFDM pilot is unrealistic to measure the channel state information. Therefore, the deterministic pilot pattern is critical for enhancing the performance and facilitating the system implementation.

B. PROBLEM FORMULATION

The sparse vector **h** can be successfully reconstructed with small amounts of measurements when the measurement matrix satisfies the well-known RIP condition. However, there is no effective method satisfying RIP for any given measurement matrix. An practicable method is to calculate the MC of the given matrix [40]. Compared with RIP, the evaluation of the MC is simpler and more practical. For a given pilot pattern, the MC of the measurement matrix **D** can be given as

$$\nu(\mathbf{D}) = \max_{\substack{1\le m,\ n\le K \\ m\ne n}} \frac{|\langle d_m, d_n\rangle|}{\|d_m\|_2\|d_n\|_2}, \tag{4}$$

where d_m and d_n are any two column vectors of the given matrix **D**. $\langle\cdot\ \cdot\rangle$ represents the inner product for the different two columns of the matrix **D**. We substitute (2) into (4), and the MC is further formulated as

$$\nu(\mathbf{D}) = \max_{\substack{1\le m,\ n\le K \\ m\ne n}} \frac{\left|\sum_{i=1}^{L} |\mathbf{S}(\Psi_i)|^2 e^{-j2\pi\Psi_i(n-m)/K}\right|}{\sum_{i=1}^{L} |\mathbf{S}(\Psi_i)|^2}. \tag{5}$$

Equation (5) reveals that the MC of the given measurement matrix **D** can be jointly determined by the pilot location and the pilot value. Assume the transmitted OFDM pilot signals are equipower $|\mathbf{S}(\Psi_1)|^2 = |\mathbf{S}(\Psi_2)|^2 = \cdots = |\mathbf{S}(\Psi_L)|^2 = 1$. By denoting $c = n - m$ and $\Delta = \{1, 2, \cdots, K-1\}$, We can further simplify (5) as

$$\nu(\mathbf{D}) = \max_{c\in\Delta} \frac{1}{L}\left|\sum_{i=1}^{L} e^{-j2\pi\Psi_i c/K}\right|. \tag{6}$$

Equation (6) demonstrates that the coherence solution of matrix is an optimization problem when the numbers of subcarriers and pilots are given. In [16]–[19], the MC minimization of the measurement matrix is an effective method to achieve better estimation performance. Therefore, according to the minimization rule of the MC, the pilot location optimization is modeled as a combinatorial problem

$$\mathbf{P}_1: \quad \min_{\Psi\in\Lambda} \ \nu(\mathbf{D}(\Psi)), \tag{7}$$

where Λ is the exhausted all pilot patterns. If the exhaustive methods are employed to generate the optimum pilot pattern, the number of available pilot patterns is $C(K, L)$, which indicates that the optimal pilot pattern cannot be obtained within a limited time [41], [42]. The core of deterministic pilot pattern optimization is quickly select the L subcarriers from the K total subcarriers, and generate the pilot pattern with the smallest MC. Therefore, it is imperative to find an efficient method for solving the optimization problem to generate an optimized deterministic pilot pattern.

III. DETERMINISTIC PILOT PATTERN LOCATION OPTIMIZATION BASED ON MQGA

Intelligent optimization algorithms are statistical search methods based on natural selection and genetic mechanism. These methods perform population operations on potential solutions and gradually generate an optimal solution with the rule of survival. The QGA is an evolutionary algorithm, which utilizes Q-bit to encode the evolved individual. In the QGA, the individuals with the superposition state are adopted to increase the diversity of the population. Quantum rotation gates are utilized to complete the update of evolution using the information of the optimal solution to guide the evolution process. Compared with the genetic algorithm, the QGA has better exploitation and exploration, and has strong global convergence using small-scale populations [43]–[47].

Instead of numeric and binary representations, the QGA employs Q-bits to represent the individuals in the population. Consider a population with n individuals, $Q(t) = \{q_1^t, q_2^t, \cdots, q_n^t\}$, where t is the generation in the evolved population. The Q-bit representation of the jth individual q_j^t in the tth generation can be defined as

$$q_j^t = \begin{bmatrix} \alpha_{j1}^t & \alpha_{j2}^t & \cdots & \alpha_{jm}^t \\ \beta_{j1}^t & \beta_{j2}^t & \cdots & \beta_{jm}^t \end{bmatrix}, \tag{8}$$

where m represents the Q-bits number. β and α represent a pair of probability amplitudes satisfied the condition $|\beta|^2 + |\alpha|^2 = 1$. For a Q-bit, $|\beta|^2$ and $|\alpha|^2$ represent the probabilities of the Q-bit state, which may be the state 0, the state 1, or two any superposition. Due to the state superposition, the Q-bit individual of the MQGA provides better diversity than the traditional binary and decimal representations.

To ensure that the evolutionary direction of the individual is towards the optimal solution, the traditional Q-gate can be utilized to update the population. In the iterative optimization process, the MQGA method is proposed that uses a new update strategy for adjusting the rotation angle to further improve the performance. This strategy ensures that each update will evolve towards the direction that is beneficial for the optimal solution. In the search space, an individual represents a pilot pattern. The Q-bit represented individual needs to be converted into a binary representation to calculate the fitness. In the process of evolution, Q-bits are collapsed in the convergent state using the maximum fitness of individual. Then, the best individual in the population refers to the optimum pilot pattern. the specific process of algorithm 1 is used to demonstrate the MQGA-based location optimization of pilot pattern.

Algorithm 1 The Deterministic Pilot Pattern Location Optimization Based on MQGA

$t \leftarrow 0$.
initialize $Q(0) = \{q_1^0, q_2^0, \cdots, q_n^0\}$.
make $P(0) = \{x_1^0, x_2^0, \cdots, x_n^0\}$ based on evaluating $Q(0)$ states.
calculate the fitness of $P(0)$.
initialize $B(0) = \{b_1^0, b_2^0, \cdots, b_n^0\}$ as the same as $P(0)$.
save the optimal solutions **b** between $B(0)$ and $P(0)$ into $B(0)$.
while (not termination-condition) **do**
  $t = t + 1$.
  obtain $P(t) = \{x_1^t, x_2^t, \cdots, x_n^t\}$ based on evaluating $Q(t-1)$.
  calculate the fitness of $P(t)$.
  make $Q(t+1)$ with the rotation gate.
  save the optimal solutions **b** between $P(t)$ and $B(t-1)$ in $B(t)$.
  update the optimal solutions **b**.
  if (migration-condition) **then**
    generate the optimized pilot pattern Ψ_{opt}.
  end if
end while
The pilot pattern $\Psi_{opt} = (\Psi_1, \cdots, \Psi_P)$ is the optimal deterministic pilot pattern.

In the population initialization stage, the probability amplitudes of individuals α and β are initialized by $1/\sqrt{2}$. Then, an individual q_j^0 represented with Q-bits provides linear superposition of all probable states based on the equal probability

$$\left|\varphi_{q_j^0}\right\rangle = \sum_{k=1}^{2^m} \frac{1}{\sqrt{2^m}} \left|S_k\right\rangle, \tag{9}$$

where S_k is the binary string that represents the kth state of an individual in the population.

During the individual evolution, we observe $Q(0)$ to make binary solution $P(0)$, where $P(0) = \{x_1^0, x_2^0, \cdots, x_n^0\}$. x_j^0, $j = 1, \cdots, n$, is m-bit binary string to represent a binary solution. The bit of the x_j^0 is obtained by selecting 0 or 1 with a random probability. We randomly provide γ between (0, 1). If $\left|\left(\alpha_{ji}^0\right)\right|^2 > \gamma$, the bit of the x_j^0 is initialized to 1, otherwise, it is initialized to 0. Although an individual represented with Q-bits has the linear superposition characteristic of all probable states, this representation method is unsuitable to evaluate the individual fitness.

In the MQGA, the fitness can describe the suitability of an individual in the population. The fitness function is a kind of the mathematical function, which is employed to determine the fitness of each individual in the population. We can define the fitness function $f(x)$ as

$$f(x) = \frac{1}{\nu(\mathbf{D})}. \tag{10}$$

During the optimization process, the weaknesses and strengths of an individual can be evaluated by the fitness function. After the fitness is calculated, $B(0) = \{b_1^0, b_2^0, \cdots, b_n^0\}$ is initialized as the $P(0)$, and the optimal solutions **b** is also saved into $B(0)$.

The optimization algorithm of the deterministic pilot pattern enters the iterative loop process. $P(t)$ can be attained based on evaluating $Q(t-1)$. The binary solution x_j^t of $P(t)$ represents a deterministic pilot pattern. Since the pilot location determines the design of a measurement matrix, we can calculate the MC of the matrix corresponding to the pilot pattern when the solutions x_j^t are given.

The optimum solutions can be formed by selecting between $B(t)$ and $P(t)$, where $B(t) = \{b_1^t, b_2^t, \cdots, b_n^t\}$. The fitness of b_j^{t-1} and x_j^t can be evaluated between $B(t-1)$ and $P(t)$ to select the optimum solutions **b** saved in $B(t)$. When the generated optimal solutions are better than **b** in $B(t)$, the saved solutions are updated by the new optimum solutions.

We employ quantum rotation gate for evolving the population from $Q(t)$ to $Q(t+1)$, which can be expressed as

$$\mathbf{G}(\phi_i) = \begin{bmatrix} cos(\phi_i) & -sin(\phi_i) \\ sin(\phi_i) & cos(\phi_i) \end{bmatrix}, \tag{11}$$

where ϕ_i represents the rotation angle to determine the state of the Q-bit. $\mathbf{G}$ is adopted for updating each Q-bit of the individuals with rotation operation. The updated $\left(\alpha'_{ji}, \beta'_{ji}\right)$ of the Q-bit can be expressed as

$$\begin{bmatrix} \alpha'_{ji} \\ \beta'_{ji} \end{bmatrix} = \mathbf{G}(\phi_i) \begin{bmatrix} \alpha_{ji} \\ \beta_{ji} \end{bmatrix}. \tag{12}$$

The rotation angle ϕ_i is given as

$$\phi_i = s(\alpha_{ji}^t, \beta_{ji}^t)\Delta\phi_i. \tag{13}$$

Table 1 demonstrates a look-up table of ϕ_i that provides the specific direction of ϕ_i in the optimization process. In [28], $\Delta\phi_i$ stands for the change of ϕ_i, which affects the optimization convergence velocity. In order to dynamically adjust the search space, $\Delta\phi_i$ is given a variable related to the generation of the evolutionary process that can be expressed as

$$\Delta\phi_i = 0.05\pi e^{-t/t_{max}}, \tag{14}$$

where t represents the current generation in the population and t_{max} defines the maximum population generation.

TABLE 1. Look-up table of the ϕ_i.

x_{ji}^t	b_{ji}^t	$f\left(x_j^t\right) > f\left(b_j^t\right)$	$s(\alpha_{ji}^t, \beta_{ji}^t)$			
			$\alpha_{ji}^t\beta_{ji}^t > 0$	$\alpha_{ji}^t\beta_{ji}^t < 0$	$\alpha_{ji}^t = 0$	$\beta_{ji}^t = 0$
0	0	false	0	0	0	0
0	0	ture	0	0	0	0
0	1	false	1	-1	0	±1
0	1	ture	-1	1	±1	0
1	0	false	-1	1	±1	0
1	0	ture	1	-1	0	±1
1	1	false	0	0	0	0
1	1	ture	0	0	0	0

$s(\alpha_{ji}^t, \beta_{ji}^t)$ can be used to describe the rotation angle direction that can guarantee the convergence of the optimization procedure. Fig. 1 shows the rotation process of Q-bit when it is stayed in the first quadrant. The updated mechanism can be described by comparing the b_{ji}^t fitness with the x_{ji}^t fitness. x_{ji}^t and b_{ji}^t represent the ith bit of the binary solution and the optimal solution, respectively. If evaluate result, $f\left(b_j^t\right) < f\left(x_j^t\right)$, is false and b_{ji}^t and x_{ji}^t are 0 and 1, the ϕ_i value can be set -1 to enhance the $|0\rangle$ probability. Otherwise, the ϕ_i value can be set $+1$ to enhance the $|1\rangle$ probability. Fig. 2 shows the update rotation process of Q-bit when it is stayed in the second quadrant. If evaluate result, $f\left(b_j^t\right) < f\left(x_j^t\right)$, is false and b_{ji}^t and x_{ji}^t are 0 and 1, the ϕ_i value can be set $+1$ to enhance the $|0\rangle$ probability. Otherwise, the ϕ_i value can be set -1 to enhance the $|1\rangle$ probability.

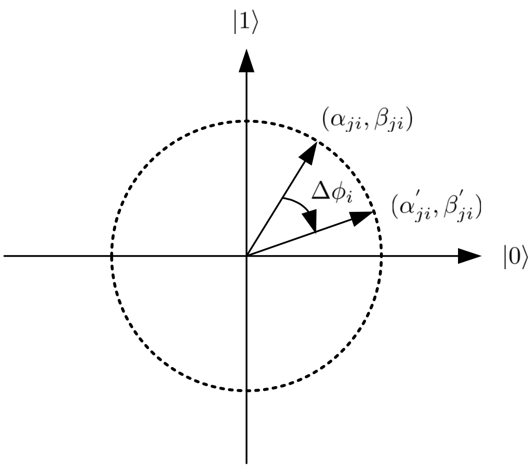

FIGURE 1. The update process of a Q-bit is described when it is stayed in the first quadrant.

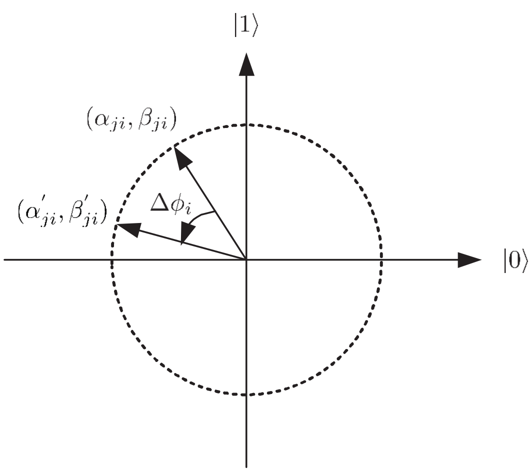

FIGURE 2. The update process of a Q-bit is described when it is stayed in the second quadrant.

Notably, the traditional genetic operators including crossover and mutation are not adopted to evolve individual in the MQGA. Although these operators can affect the observation probability of the individual's linear state, the Q-bit individual essentially has a linear superposition state. Therefore, these genetic operators are unnecessary in the MQGA. During the iterative optimization process, the pilot pattern optimization algorithm will terminate and obtain the optimal solution when the termination conditions are satisfied.

IV. SIMULATION RESULTS

The deterministic pilot patterns are provided to evaluate the estimation performance with different modulations. The parameters of the digital radio mondiale (DRM) [48] are used to complete the simulations, which are shown in Table 2. The sparse reconstruction methods have been adopted to OFDM sparse channel estimate. The orthogonal matching-pursuit (OMP) [49]–[51] is a typically adopted the reconsitution algorithm to reconstruct the sparse vector **h** since it is the most widely used in various sparse recovery systems [52]–[56]. For comparison, the equispaced pilot patterns are provided for the standard LS estimation approach.

TABLE 2. System parameter.

parameter	type B	type C
sample period	83.3 us	83.3 us
symbol duration	26.66 ms	20 ms
FFT length	256	176
subcarriers	256	176
guard interval	5.33 ms	5.33 ms
frame duration	400 ms	400 ms
pilots	26	26
multipaths	4	4
modulation	QAM, 64QAM	QAM, 64QAM
Signal to Noise Ratio (SNR)	0-30 dB	0-30 dB

Channel 3 in the DRM is adopted as a sparse multi-path channel since it is a typical multipath channel model. Table 3 lists the specific parameters of channel 3. For the coefficients of channel response, four non-zero taps are randomly provided, where the gain of the taps satisfies an independent Gaussian distribution. It can be observed from the DRM parameters that the designed subcarrier channel is a frequency non-selective and slow fading channel. Therefore, the wireless channel will generate the same influence on each transmitted OFDM symbol, which reduces the complexity of channel estimation.

TABLE 3. Sparse channel parameter.

parameter	path 4	path 3	path 2	path 1
delay	2.2 ms	1.5 ms	0.7 ms	0
gain	0.25	0.5	0.7	1
doppler-shift	1.0 Hz	0.5 Hz	0.2 Hz	0.1 Hz
doppler-spread	2.0 Hz	1.0 Hz	0.5 Hz	0.1 Hz

To initialize the population, $n = 1000$ and $t = 10000$ are set. These populations are used in the genetic algorithms. For the optimization methods of QGA and MQGA, the individual probability amplitudes are initialized to $1/\sqrt{2}$.

Same parameters are set for the random search optimization method [16]. Table 4 lists the deterministic pilot patterns generated by different optimization methods. It can be observed from Table 4 that the MC value of the generated measurement matrices by the various pilot patterns decreases from 0.2418 and 0.2936 to 0.1234 and 0.1382. Obviously, the MQGA-based optimization method provides the smallest MC, which proves that the proposed optimization method substantially improves the design of measurement matrix.

TABLE 4. The optimized various pilot patterns.

type	method	MC	pilot patterns								
			2	14	20	26	29	36	51	64	67
	random	0.2418	72	78	85	93	107	119	135	141	149
			160	166	170	174	185	192	227	247	
			2	4	10	17	26	32	36	54	58
	GA	0.2248	64	70	74	100	108	111	114	121	133
			135	141	157	161	171	187	228	246	
			3	8	10	15	25	33	40	48	56
B	MAGA	0.2052	61	88	97	127	139	144	161	167	186
			192	195	202	212	220	225	235	252	
			5	11	33	62	69	71	82	101	109
	QGA	0.1411	117	124	137	146	152	159	167	179	181
			193	204	216	219	222	235	247	253	
			17	24	29	39	46	54	62	78	94
	MQGA	0.1234	100	136	131	139	147	155	164	173	181
			188	197	215	224	232	240	247	255	
			3	4	6	15	21	23	24	40	46
	random	0.2936	50	56	61	73	84	90	94	99	100
			119	134	147	152	165	167	172	175	
			1	2	17	20	30	52	58	63	72
	GA	0.2308	79	84	94	100	105	109	110	116	120
			129	131	133	138	144	150	154	173	
			3	19	22	31	39	50	55	60	64
C	MAGA	0.1944	72	87	90	95	99	105	109	113	117
			123	127	130	135	142	151	164	167	
			3	8	16	21	29	32	37	41	48
	QGA	0.1437	53	60	66	71	77	91	102	109	114
			121	125	132	144	147	156	163	172	
			4	10	13	23	26	33	39	44	51
	MQGA	0.1382	56	62	67	74	79	85	96	103	112
			127	133	136	147	150	164	169	172	

The estimation performance can be evaluated with the optimized various pilot patterns by 1000 Monte Carlo trials. Figs. 3 and 4 show the mean-square-error (MSE) and bit-error-rate (BER) curves of various pilot patterns over channel 3 under robust mode B, respectively. The results show that the MQGA-based optimization method outperforms the other methods such as random search scheme and the conventional genetic algorithms. Since the measurement matrix determined with the equispaced pilot patterns has a larger MC, which reduces the reconstruction performance of the sparse recovery algorithms.

It is shown from Fig. 3 that the performance curves obtained by the genetic algorithms are better than the random search approach. We can observe that the MQGA-based approach has the best MES performance since this scheme

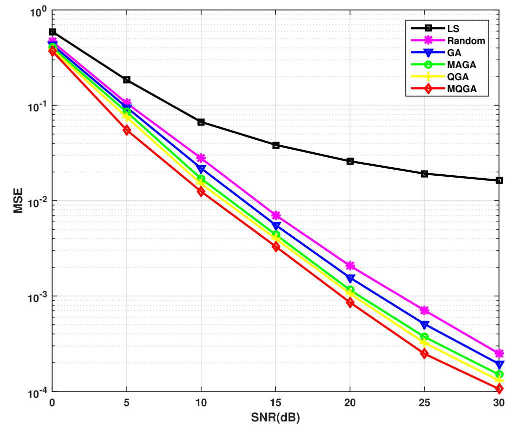

FIGURE 3. Performance comparisons of MSE versus SNR by various pilot patterns over channel 3 under robust mode B, which is modulated with QAM.

can obtain a measurement matrix with a smaller MC. This reveals that random pilot patterns do not always ensure performance and it is important to optimize the pilot location using the minimum coherence rule. It can be observed from Fig. 4 that BER of the optimization method using the MQGA approach is lower than the other optimization schemes.

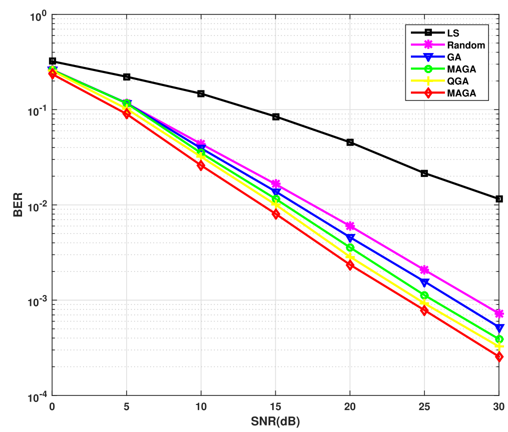

FIGURE 4. Performance comparisons of BER versus SNR by various pilot patterns over channel 3 under robust mode B, which is modulated with QAM.

Figs. 5 and 6 depict the MSE and BER performance curves obtained from various pilot patterns over channel 3 under robust mode C, respectively. Comparing the considered optimization methods, the pilot pattern optimized based on MQGA achieves the best performance that verifies the effectiveness of the proposed scheme. We can observe from the Fig. 6 that the gain of the MQGA shceme is 5dB higher than the random search scheme when BER= 0.001. The channel coding at the receiver can eliminate bit errors when the BER is lower than 0.01. Therefore, for exploiting the channel sparsity, the MQGA-based pilot optimization method outperforms the other methods.

Furthermore, in order to evaluate the validity of the generated pilot pattern for higher modulations, the MSE and

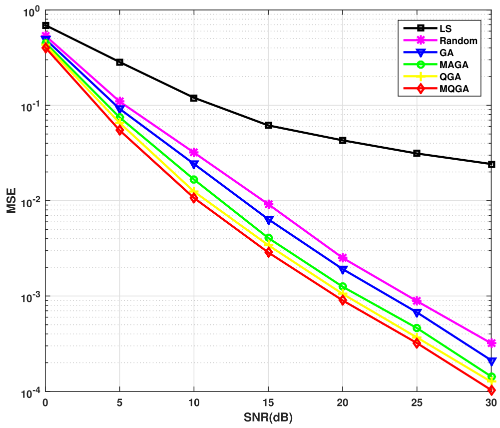

FIGURE 5. Performance comparisons of MSE versus SNR by various pilot patterns over channel 3 under robust mode C, which is modulated with QAM.

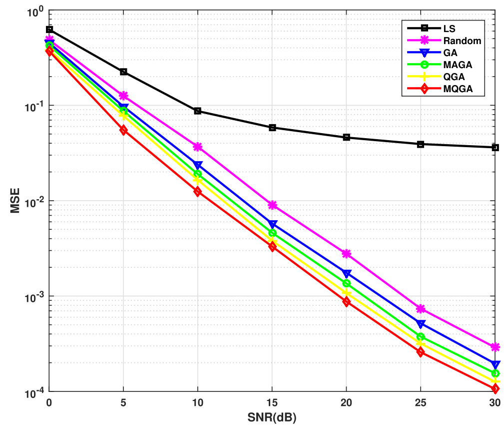

FIGURE 7. Performance comparisons of MSE versus SNR by various pilot patterns over channel 3 under robust mode B, which is modulated with 64QAM.

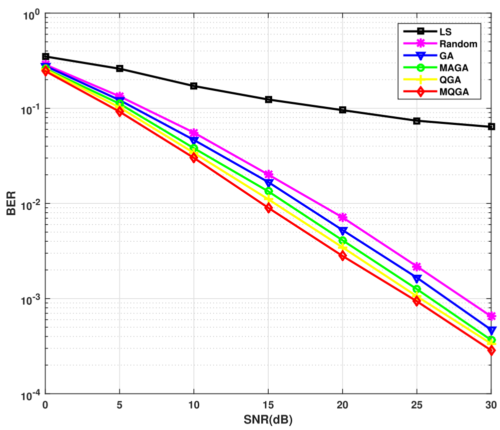

FIGURE 6. Performance comparisons of BER versus SNR by various pilot patterns over channel 3 under robust mode C, which is modulated with QAM.

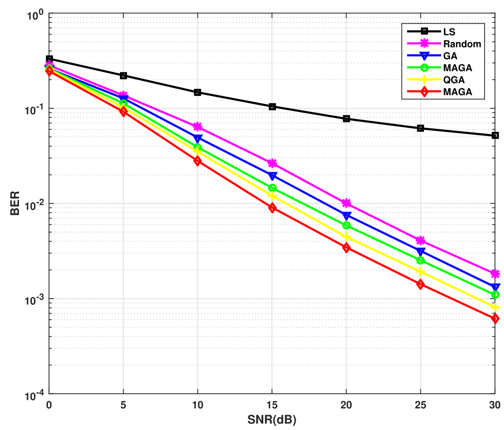

FIGURE 8. Performance comparisons of BER versus SNR by various pilot patterns over channel 3 under robust mode B, which is modulated with 64QAM.

BER performances are compared by various pilot patterns over channel 3 under robust mode B that is modulated with 64QAM. Figs. 7 and 8 show the MSE and BER of six pilot optimization methods, respectively. Clearly, the LS method achieves the worst evaluated estimation performance. As the SNR increases, the proposed MQGA-based optimization scheme obtains the best performance in terms of BER and MSE.

Figs. 9 and 10 exhibit the performance curves of the sparse reconstruction by various pilot patterns over channel 3 under robust mode C. As it can be shown from the figures, the LS method with equispaced pilot patterns yields the worst reconstruction performance. The superior performance of the MQGA-based optimization method demonstrate its feasibility and effectiveness. In MQGA algorithm, the generated measurement matrix provides lower MC using individual optimization, which can effectively improve the recovery accuracy for OMP reconstruction algorithm. It means that even though the order of modulation is escalated from QAM to 64QAM, the optimized pilot pattern can provide its performance superiority on both MSE and BER. Therefore, the MQGA-based optimized method is also effective for OFDM sparse channel estimation with higher modulation. The above-mentioned results demonstrate and validate that the proposed MQGA-based optimization method outperforms random scheme, GA, MAGA and QGA with forming superior performance measured by MSE and BER.

The computer runtimes for various pilot optimization schemes are listed in Table 5. The simulation environment utilizes the MATLAB R2018b with 8 GB memory and a quad-core 3.9 GHz CPU. As it can be shown from the Table 5, the MQGA-based optimization method takes less time than the random search. Quantum algorithms consume more time than the traditional genetic algorithms. Although the individual represented by Q-bit enhance the diversity of population, this representation approach is unsuited to evaluate individual fitness. In the QGA, the Q-bit represented individual needs to be converted into a binary representation to calculate the fitness, which greatly influences the convergence time. Hence, the update strategy of the rotation angle is adjusted

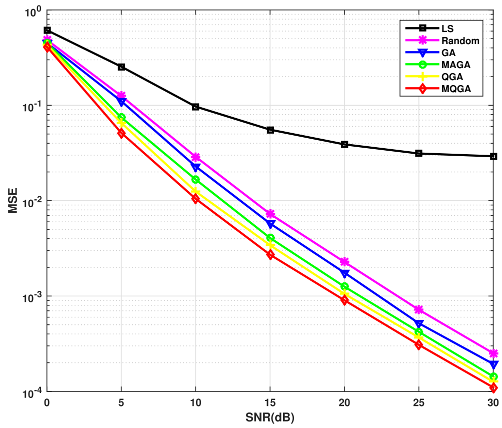

FIGURE 9. Performance comparisons of MSE versus SNR by various pilot patterns over channel 3 under robust mode C, which is modulated with 64QAM.

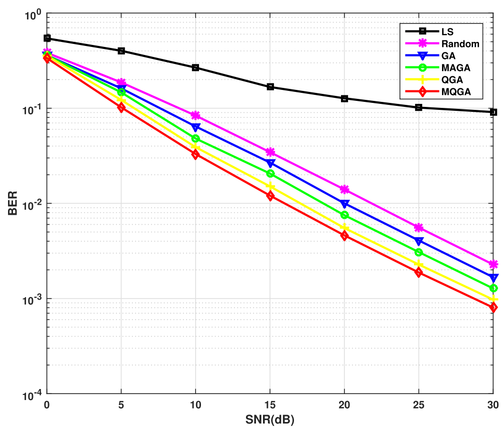

FIGURE 10. Performance comparisons of BER versus SNR by various pilot patterns over channel 3 under robust mode C, which is modulated with 64QAM.

TABLE 5. The various schemes runtimes.

type	method	time (s)
B	random [11]	480
	GA	115
	MAGA [17]	280
	QGA	423
	MQGA	385
C	random [11]	425
	GA	75
	MAGA [17]	214
	QGA	369
	MQGA	330

in the MQGA. The rotation angle of the MQGA is defined as a variable related to the population generation, which effectively reduces the update time compared to QGA.

It is worth mentioning that the OFDM pilot signal design is offline achieved at the transmitter. The performance of channel estimation is the most critical part for an OFDM system. Therefore, the recommended location design of the deterministic OFDM pilot pattern is entirely feasible.

V. CONCLUSION

In this paper, the location optimization of the deterministic pilot pattern is investigated using the minimum MC rule to design the measurement matrix. The design of the deterministic OFDM pilot pattern can be summarized as an combinatorial problem. The convergence time of the QGA is improved by adjusting the update strategy of the rotation angle. The proposed MQGA-based optimization method employs individual evolution to realize the update and optimize the pilot position. The obtained results shown that our approach can form excellent measurement matrix with a smaller MC and provide better estimation performance compared with the genetic algorithms and random search method. In future, the authors plan to focus on pilot pattern optimization rule and intelligent search methods. In addition, intelligent channel estimation method employing deep learning in the wireless communication will be investigated.

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