Quantum-entanglement pigeon-inspired optimization for unmanned aerial vehicle path planning

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Abstract

Purpose – The purpose of this paper is to propose a new algorithm for independent navigation of unmanned aerial vehicle path planning with fast and stable performance, which is based on pigeon-inspired optimization (PIO) and quantum entanglement (QE) theory.

Design/methodology/approach – A biomimetic swarm intelligent optimization of PIO is inspired by the natural behavior of homing pigeons. In this paper, the model of QEPIO is devised according to the merging optimization of basic PIO algorithm and dynamics of QE in a two-qubit XXZ Heisenberg System.

Findings – Comparative experimental results with genetic algorithm, particle swarm optimization and traditional PIO algorithm are given to show the convergence velocity and robustness of our proposed QEPIO algorithm.

Practical implications – The QEPIO algorithm hold broad adoption prospects because of no reliance on INS, both on military affairs and market place.

Originality/value – This research is adopted to solve path planning problems with a new aspect of quantum effect applied in parameters designing for the model with the respective of unmanned aerial vehicle path planning.

Keywords Pigeon-inspired optimization (PIO), Quantum entanglement, Quantum entanglement pigeon-inspired optimization (QEPIO), Unmanned aerial vehicle (UAV)

Paper type Research paper

1. Introduction

Recently, researchers conduct different approaches concerning independent navigation and flight planning problems on unmanned aerial vehicle (UAVs) (Ergezer and Leblebicioglu, 2013; Duan *et al.*, 2013). For instance, gravitational search algorithm is enhanced by fuzzy controller to command mutation parameter (Kherabadi *et al.*, 2017). The adaptive differential evolution algorithms (DE) are further developed for the multi-objective optimization problems (Wang and Tang, 2016; Brest, 2016). Multi-agent system is adopted to accommodate the algorithm to support bilateral selections between individuals and subpopulations (Zhang and Wong, 2013). The improved particle swarm optimization (PSO) algorithms are used for global search or rotational invariant strategy to explore the rotation variance property of the search space (Chen *et al.*, 2013; Tanweer *et al.*, 2016; Ali and Tawhid, 2016). Crisscross search PSO (CSPSO) is proposed for accelerating the global convergence of PSO through horizontal and vertical crossover (Meng *et al.*, 2016).

Among the current optimization algorithms, there are several considerations for path computation, including convergence property, computational complexity, optimality, etc. (Duan *et al.*, 2010; Garcia *et al.*, 2013). While the general representatives above are capable to reach the relatively mature optimization results, there is still room for improvement on convergence velocity and the overall robustness of path planning (Duan and Li, 2014).

The path of UAVs can be assumed by a series of computational nodes, with the main determinant of optimal approach. This category of problem can be served by a swarm intelligence optimizer (Zhao *et al.*, 2012), which works with a population of particles like PSO (Cai *et al.*, 2014). Based on the specific navigation behavior of pigeon flight in nature, Duan and Qiao proposes a new pigeon-inspired optimization (PIO) algorithm (Duan and Qiao, 2014). Compared to Genetic algorithm (GA) and PSO, the basic PIO algorithm manifests faster convergence velocity and avoidance of information points (Hao and Duan, 2014; Changhao and Duan, 2013). Meanwhile, based on the PIO algorithm, several studies have indicated a neurodynamic approach for image restoration (Duan and Wang, 2015), hypersonic vehicles (Xue and Haibin, 2017), quantum spin optimization (Li and Duan, 2014), etc.

Through the present algorithms above, we can figure out a critical problem that this class of algorithms generally bring on uncertainty of parameters, with unexpected performance of robustness. Meanwhile, they are almost considered in traditional dynamics field. Now we try to find a new method for

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Aircraft Engineering and Aerospace Technology
91/1 (2019) 171–181

[DOI 10.1108/AEAT-03-2018-0107]

Received 20 March 2018
Revised 12 June 2018
21 June 2018
Accepted 21 June 2018

optimization controlling through the integration with the concept of quantum field.

Quantum entanglement (QE) is a quantum mechanics phenomenon, which plays a vital role in quantum computing and quantum communication (Nielson and Chuang, 2000). It describes the entanglement of several particles which are independent of localization. Even if they are far apart in distance, the behavior of a single particle will affect the state of others, both in the ways of thermodynamics and kinetics (Kurzyk, 2012), bringing with instantaneous corresponding state changes (Lockhart *et al.*, 2017). QE is always regarded as a non-local "information source", with continuous leakage to the environment (Wang *et al.*, 2013; Kielpinski *et al.*, 2013).

In recent years, quantum technology has accomplished several breakthroughs, with the following researches mainly on the degree of QE C. In Milburn's intrinsic decoherence theory (Milburn, 1991), it shows the effect of external magnetic field on entanglement in the existence of intrinsic decoherence. Qian investigates the effect of interaction vector for entanglement Dzyaloshinskii–Moriya (DM) on two-particle Ising model when considering intrinsic decoherence (Qian and Fang, 2009). Xie discusses the impact of anisotropy on performance of QE with Heisenberg XYZ chains case of two particles (Li-Jun *et al.*, 2009). In the current field for application, the development of Quantum Key Distribution and other aspects are further advanced (Liu and Deng, 2016).

In our paper, we will further consider the flight planning based on merging QE theory of two-particle XXZ Heisenberg system (Guo *et al.*, 2014) with the conventional PIO algorithm.

This article will be discussed in the following sections. In the next section, we first introduce the two-particle Heisenberg system XXZ model, and launch the equation of QE from different entangled initial states. In the third section, we briefly introduce two processes of traditional PIO algorithm – map and compass operator and landmark operator. Then, we do hypotheses of QEPIO algorithm, including underlying assumptions and further assumptions based on QE theory in the fourth section. In the fifth section, we figure out the analysis of convergence and complexity of QEPIO and put forward the logic process. In the sixth section, simulations are conducted on QE evolution, choice of switching point and the results of proposed QEPIO optimization algorithm, compared with the traditional PIO, DE, GA and PSO algorithm on convergence velocity and robustness. The comparison results show great improvement on features of convergence and consistence. Eventually, we will discuss the general prospect of QEPIO algorithm in military and civil field, and possible further research direction for algorithm optimization on multi-QE.

Quantum entanglement in a two-qubit XXZ Heisenberg system

With the external conditions changing, Heisenberg system can evolve XY, XXZ and other dynamic models (Kloc *et al.*, 2017; Barenco *et al.*, 1995). In this paper, we will use the two-particle Heisenberg XXZ model theoretically for further integrating research.

The Hamiltonian H of the two-particle XXZ Heisenberg model can be expressed as follows (Santos, 2003):

$$\mathbf{H} = \frac{1}{2}\Big[\mathcal{J}\big(\boldsymbol{\sigma}_1^x\boldsymbol{\sigma}_2^x + \boldsymbol{\sigma}_1^y\boldsymbol{\sigma}_2^y + \Delta\boldsymbol{\sigma}_1^z\boldsymbol{\sigma}_2^z\big) + B\big(\boldsymbol{\sigma}_1^z+\boldsymbol{\sigma}_2^z\big) + D\big(\boldsymbol{\sigma}_1^x\boldsymbol{\sigma}_2^y - \boldsymbol{\sigma}_1^y\boldsymbol{\sigma}_2^x\big)\Big] \quad (1)$$

Where $\boldsymbol{\sigma}_\mathbf{i} = (\boldsymbol{\sigma}_\mathbf{i}^x, \boldsymbol{\sigma}_\mathbf{i}^y, \boldsymbol{\sigma}_\mathbf{i}^z)$ is the bubble matrix operator, $\mathcal{J}$ is the coupling coefficient, D is the module of the DM interaction vector parameter (Hu *et al.*, 2011), Δ is the dimensionless coefficient that characterizes the anisotropy of this system, and B expresses the strength of the applied magnetic field.

Under the two particle bases $\{|00\rangle, |01\rangle, |10\rangle, |11\rangle\}$, the Hamiltonian H can be expressed as:

$$\mathbf{H} = \begin{pmatrix} \frac{\mathcal{J}\Delta}{2} + B & 0 & 0 & 0 \\ 0 & -\frac{\mathcal{J}\Delta}{2} & \mathcal{J} + iD & 0 \\ 0 & \mathcal{J} - iD & -\frac{\mathcal{J}\Delta}{2} & 0 \\ 0 & 0 & 0 & \frac{\mathcal{J}\Delta}{2} - B \end{pmatrix} \quad (2)$$

We can obtain the eigenvalues of the corresponding Hamiltonian from the above matrix, and then obtain the following corresponding eigenstates:

$$\begin{cases} |\psi_1\rangle = |00\rangle \\ |\psi_2\rangle = |11\rangle \\ |\psi_3\rangle = \frac{\sqrt{2}}{2}[\exp(i\theta|01\rangle + |10\rangle)] \\ |\psi_4\rangle = \frac{\sqrt{2}}{2}[-\exp(i\theta|01\rangle + |10\rangle)] \end{cases} \quad (3)$$

In the above equation, $\theta = \arctan(D/\mathcal{J})$.

Milburn argues that the quantum system process is a random sequence evolution, with a modified Schrodinger equation for quantum decoherence factor in energy eigenstates, i.e. the intrinsic decoherence model described above (Milburn, 1991). Based on the time-density matrix $\rho(t)$ (Guo *et al.*, 2014), three initial system assumptions in the study of QE systems are shown below:

- If the initial state of QE system is a separate state $|\psi(0)\rangle = |00\rangle$ or $|\psi(0)\rangle = |11\rangle$, then the degree of system entanglement $\boldsymbol{C}$is always equal to 0; (where $|1\rangle$ and $|0\rangle$ respectively represent the upward and downward spin state of a single quantum).
- If the initial state of QE system is $|\psi(0)\rangle = a|00\rangle+b|11\rangle$ (a, b are parameters), then the system entanglement is unrelated to the value of the DM interaction and has time-independent evolution relationship with external magnetic field and intrinsic decoherence γ. Among them, when $a = b = \sqrt{2}/2$, known as the maximum entangled state, the evolution is attenuated to zero at different rates with the effect of field strength B (when B is zero, the system entanglement is always the maximum).
- If the initial state of QE system is $|\psi(0)\rangle = c|01\rangle + d|10\rangle$ (c, d are parameters), then the entanglement degree C is not related to any anisotropy parameter and applied magnetic field. Instead, it is strongly influenced by DM

and the intrinsic decoherence factor γ, with the characteristics of time-independent evolution.

In this paper, we focus on the common state threeof the entangled system. Thus, the numerical entanglement analysis based on state threeis embedded into the traditional pigeon optimization algorithm (basic PIO) to form a PIO optimization algorithm based on QE (i.e. QEPIO):

By the definition of two-particles, entanglement proposed by W.K (Kloc *et al.*, 2017), in the initial state ($|\psi(0)\rangle = c|01\rangle + d|10\rangle$), the entanglement degree C is:

$$\mathbf{S} = \exp(-i\theta)\Big\{cd\cos\theta - \frac{c^2 - d^2}{2}i\exp\left[-2\gamma\mathbf{t}(\mathcal{J}^2 + D^2)\right] \times \sin\left(2\sqrt{\mathcal{J}^2 + D^2}\mathbf{t}\right) + icd\,sin\,\theta\,cos\left(2\sqrt{\mathcal{J}^2 + D^2}\mathbf{t}\right) \times \exp[-2\gamma\mathbf{t}(\mathcal{J}^2 + D^2)]\Big\}. \quad (4)$$

$$\mathbf{C} = 2\max(0, |\mathbf{S}|) \quad (5)$$

Where S is related to time-density matrix.

In the fourth section, we will use the conclusion above to devise the QEPIO algorithm optimization through certain hypotheses.

Basic pigeon-inspired optimization

The basic PIO algorithm is originated from the phenomenon of pigeon's independent navigation, and mainly determined by two operators: map and compass operator and landmark operator (Duan and Qiao, 2014).

Map and compass operator

In nature, pigeons in homing process will experience different stages of nerve feedback, and make the use of magnetic fields and landmarks to find their flight path. The map and the compass operator is the magnetic field factor in which occur at the beginning of the stages (the actual time for neural feedback will be replaced by the amount of iteration $N_{C\max1}$ in our model). In the basic PIO, we process this map and the compass operator in certain iterations and help virtual "pigeons" (i.e. each coordinate placement) confirm the real-time position $\mathbf{x_i}$ and velocity vector $\mathbf{v_i}$ after iterations of t.

Before the formal operation of iterations, initialization should be set. The total number of virtual "pigeons" N, the number of iterations of the map and the compass stage $N_{C\max1}$, and the factor of map and the compass operator R are assigned. By PSO theory and initialization conditions, we obtain:

$$\mathbf{v_i}(\mathbf{t}) = \mathbf{v_i}(\mathbf{t}-\mathbf{1}) \times e^{-R\mathbf{t}} + rand \times \left(\mathbf{x_g} - \mathbf{x_i}(\mathbf{t}-\mathbf{1})\right) \quad (6)$$

$$\mathbf{x_i}(\mathbf{t}) = \mathbf{x_i}(\mathbf{t}-\mathbf{1}) + \mathbf{v_i}(\mathbf{t}) \quad (7)$$

Where $rand$ is a random figure and $\mathbf{x_g}$ is the current global optimal coordinate, which can be obtained by comparing the current position of all virtual "pigeons". In the simulation operation, it will reflect in the fitness function for all the "pigeons" coordinating relative to the target position.

In map and compass operator, if we assume a rightmost "pigeon" with the current global optimal position, then each virtual "pigeon" will have a direction vector towards to the rightmost "pigeon". In the coordinate system, it is reflected by other coordinates vector pointing to the rightmost point. Meanwhile, each virtual "pigeon" itself retains a velocity vector in the iteration of $\mathbf{t-1}$. Thus, in the iteration of t, the velocity of each virtual "pigeon" is the speed of the former multiplied by the factor e^{-RT}, and do vector summation with the velocity pointing to the current global optimal coordinate multiplied by a random number, reflected in the figure for the two arrows and the direction of the vector superposition of the results.

Landmark operator

In the landmark operator process, the purpose is to imitate the influence of the actual landmark navigation on pigeon's autonomous navigation. The core is selection for the global center coordinate. After the iterations of map and compass operator, the current real-time position $\mathbf{x_i}$ and velocity vector $\mathbf{v_i}$ will be transferred to the new landmark operator process with iterations of $N_{C\max2}$. The natural mechanism is that some of the pigeons are familiar with the path and hold narrow deviation value, while some of the pigeons are in an unknown path and need to observe flight position and direction of the "lead" pigeon then to decide whether to correct their current speed direction.

Reflected in the PIO algorithm, we take the "abandonment" principle of halving the current number of pigeons in each iteration for this operator cycle. The reason why we abandon half of the number (1/2) instead of 1/4 or 1/3 is for the tendency to decrease the possible iterations, to better control the time complexity of the proposed algorithm, which depends on iterations times to a weighted extent (with more relative details shown in Table I). Then we use the "center" best position $\mathbf{x_C}$ of the retaining pigeons as a moving landmark to determine the current flight speed reference direction vector, according to the following formula:

$$\mathbf{N}(\mathbf{t}) = \mathbf{N}(\mathbf{t}-\mathbf{1})/2 \quad (8)$$

Table I Comparison results on time complexity of algorithms

Algorithm	Time complexity
GA	$O\left(2N_PN_C\sum_{m=1}^{D}CodeL_m + \frac{3}{2}N_PD\right)$
PSO	$O(DN_PN_C)$
Basic PIO	$O(DN_PN_C + N_{C\max2}N_P\log{}_2N_P)$
QEPIO	$O(DN_PN_C + N_{C\max2}N_P\log{}_2N_P)$

Notes: Similarly, we can figure out the computation complexity of PSO algorithm by calculating the effecting factors for updating process, correlating with dimensionality, amount and iterations; we obtain the computation complexity of GA algorithm through procedure analysis of deciphering, selecting and copying, intersecting and variation, where $CodeL_m$ in the formula is the threshold figure of the m^{th} dimension; we postulate that the time complexity is basically determined by the worst time complexity

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$$\mathbf{x_C}(\mathbf{t}) = \frac{\sum \mathbf{x_i}(\mathbf{t}) \times fitness(\mathbf{x_i}(\mathbf{t}))}{N \times \sum fitness(\mathbf{x_i}(\mathbf{t}))} \tag{9}$$

$$\mathbf{x_i}(\mathbf{t}) = \mathbf{x_i}(\mathbf{t-1}) + rand \times \left(\mathbf{x_C}(\mathbf{t}) - \mathbf{x_i}(\mathbf{t-1})\right) \tag{10}$$

where $\mathbf{x_C}(\mathbf{t})$ is the "center" optimal position after retaining half of the pigeons and is calculated from the fitness function. In simulations, the fitness function $fitness(\mathbf{x_i}(\mathbf{t}))$ is determined by the dimension and the actual problem:

$$fitness(\mathbf{x_i}(\mathbf{t})) > 0$$

$$\begin{aligned} fitness(\mathbf{x_i}(\mathbf{t})) &= \frac{1}{f_{\min}(\mathbf{x_i}(\mathbf{t})) + \varepsilon} \quad (\text{min.}) \\ fitness(\mathbf{x_i}(\mathbf{t})) &= f_{\max}(\mathbf{x_i}(\mathbf{t})) \ (\text{max.}) \end{aligned} \tag{11}$$

In this part of algorithm, the operation coordinate $\mathbf{x_i}(\mathbf{t})$ is similar to that of the landmark and the map operator. min. stands for minimization issues and max. stands for maximization issues.

Assumptions

In this paper, to further simplify and optimize the problem, several assumptions of the QEPIO optimization algorithm are made.

Basic assumptions

- As we mainly focus on the combination of QE theory and conventional PIO algorithm, we regard every UAV as a particle in two-dimensional environment for simplification and better comprehension.
- All virtual "pigeons" have the ability to self-compute map and compass operator and landmark operator, which is reflected in nature to perceive the sun, geomagnetic fields, surrounding landmarks and lead pigeons.
- All virtual "pigeons" move in a given border zone. If beyond the border it will hold the flight direction of the border line.
- All virtual "pigeons" in the iterative operation process will not be affected by other external factors, such as other disturbance changes.

Specific assumptions for quantum-entanglement pigeon-inspired optimization model

- The pigeon and the environment are overall regarded as a QE system, and each virtual "pigeon" is defined as a single quantum in our operation.
- Based on the dynamic process of the two-particle Heisenberg XXZ model, we consider that the evolution process of each virtual "pigeon" entangles with the current global optimal position.
- We assume that the initial state for QE system is $|\psi(0)\rangle = c|01\rangle + d|10\rangle$, as it holds high possibility and obvious characteristic of quantum system. The evolution is mainly affected by the DM interaction degree D and the intrinsic decoherence factor γ, with the characteristic of time-independence.
- Considering the given value of DM interaction degree D and the intrinsic decoherence factor γ, we can control the given range of parameters D and γ, and then obtain the convergence result of the evolution of the QE with time (i.e. the number of iterations)

Quantum-entanglement pigeon-inspired optimization

On the basis of assumptions above, in this section, we will first analyze the convergence and computation complexity, and then discuss the procedure and make the logic flow of the proposed QEPIO algorithm.

Convergence and complexity analysis of the quantum-entanglement pigeon-inspired optimization algorithm

By the basic theory of Markov Chain (Athreya and Ney, 1978) and definition of global optimal solution set $\boldsymbol{M}$, we can obtain that the Markov Chain of the PIO algorithm can converge to the global optimal solution sets $\boldsymbol{M}$, i.e. $\lim_{x\to\infty} P\{X(t) \in \mathrm{M}\} = 1$, where $\mathbf{X}(\mathbf{t})$ is the instantaneous coordinate state (Zhang and Duan, 2017). In our QEPIO algorithm, through QE merging, we can use equations (4) and (5) to control the effecting factor for fore iterations with certain rules, rather than a random figure on potentially high or low value. Accordingly, it is more easily to reach the appeal point, which means the QEPIO algorithm can converge to the global optimized solution set $\boldsymbol{M}$.

From the mathematical description of compared algorithms, we can figure out the computation complexity to make further analysis on the performance of computation cost. For the space complexity, its memory space is only affected by the number of variables embodied by the operating manners, regardless of the number of iterations or the total number of virtual "pigeons". In other words, the variables could be almost classified into the functions of (t) and (t-1) or the optimum with constant amount of variables and changing values, instead of a matrix with continuous increase of variables affected by iterations. Given this situation, we focus more on time complexity.

Concerning the basic PIO algorithm, time complexity of the map and compass operator for one generation is $O(DN_p)$, as we need to update every dimensionality of every "pigeon". While, time complexity for the landmark operator on one generation is $O(DN_P+N_P log_2 N_P)$, for the reason that N_P is halved on every new iteration. Thus, the time complexity of basic PIO algorithm should be $O(DN_P N_C+N_{C\max2} N_P log_2 N_P)$. Where N_C is the whole number of iterations, and $N_{C\max2}$ is the number of iterations for landmark operator.

If we take the degree of QE $\boldsymbol{C}$ into account, we only change the computing formula instead of the running cycles. In other words, for QEPIO algorithm, when the convergence property runs better, the time complexity holds the same as basic PIO, which sufficiently manifests the comprehensive performance of QEPIO.

The comparison results on time complexity of four kinds of algorithms are shown in Table I. Apparently, GA algorithm shows weakness on time complexity compared with PSO or derivatives of PIO. While PSO algorithm shows its merit on time complexity, the converging velocity of PSO in limited

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iterations may be not as expected, which will be discussed in the 6th section in detail.

Procedure of quantum-entanglement pigeon-inspired optimization algorithm

The core of our QEPIO optimization approach is to replace the random component in the velocity operation over a period of iterations by our method of QE merging. The procedure of QEPIO algorithm is as below.

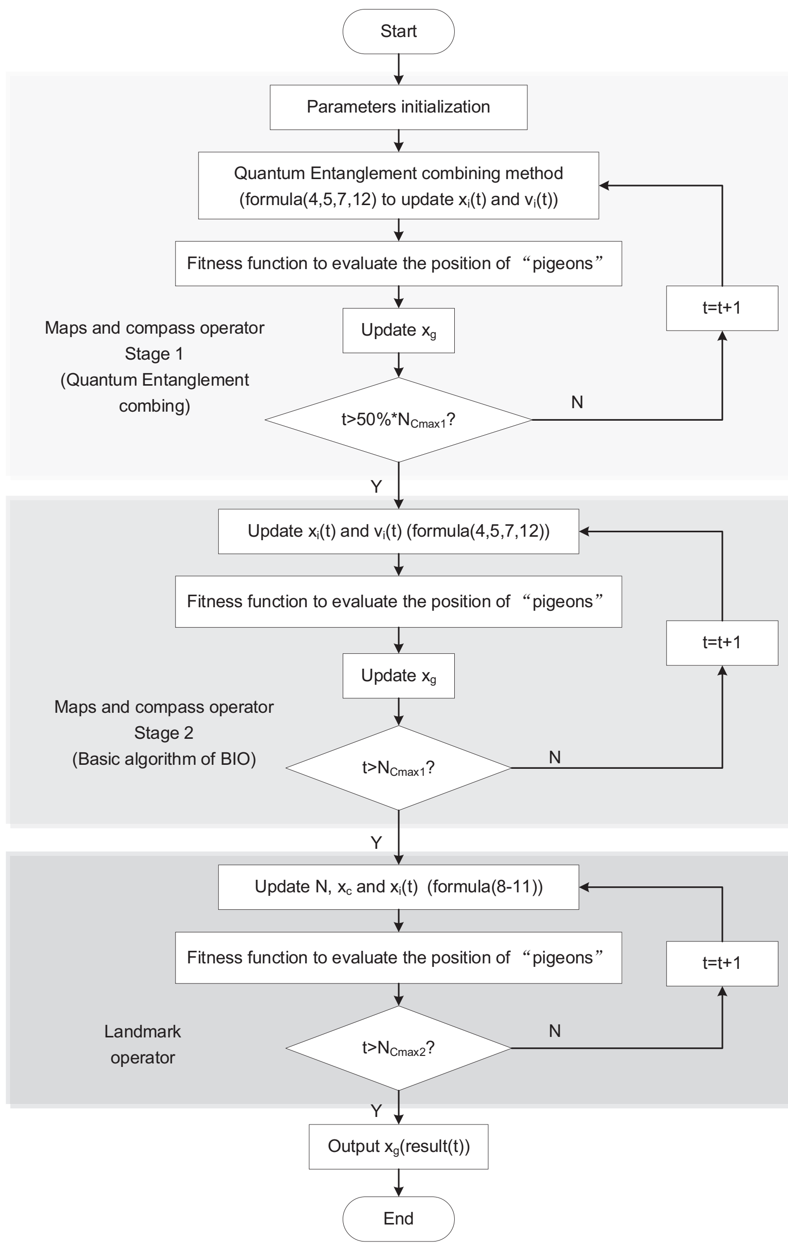
Initial

- *Step 1*. Keep the general direction of two independent iterative process, and set the initial conditions of the system: Set the number of iterations N_{cmax1}, N_{cmax2}, the number of pigeons N, the system dimension D_1, the map and the compass factor R and the boundary selection, which are equivalent with the basic PIO. In addition, select the intrinsic decoherence coefficient and DM interaction vector parameter D reasonably.
- *Step 2*. Assign the random figures of initial velocity and boundary position for each virtual "pigeon", and compare the initial fitness of all virtual "pigeons" with the fitness function. Then, select the current optimal position coordinate point, as the initial coordinate .

Procedure of map and compass operator

- *Step 3*. Process of the map and compass operator – the first stage.

Figure 1 Flow chart of QEPIO algorithm



First, update the speed and position of all coordinate points. When the number of iterations t is less than 50 per cent of the total number of iterations $N_{C\max1}$ for the first stage, the operation follows equations (4), (5), (7) and (12) as follows:

$$\mathbf{v_i}(\mathbf{t}) = \mathbf{v_i}(\mathbf{t}-\mathbf{1}) \times e^{-R\mathbf{t}} + \mathbf{C} \times \left(\mathbf{x_g} - \mathbf{x_i}(\mathbf{t}-\mathbf{1})\right) \tag{12}$$

That is, to retain the original operation of the basic method, and apply the degree of QE $\boldsymbol{C}$ of current each pigeon with the current global optimal coordinate point, which replaces the original rand random number. As the parameter itself (i.e. *rand* in former basic PIO method) is to reflect the influence of current global optimal coordinate on each pigeon, based on the uncertainty of the second law of general dynamics. In the quantum system, indeed, the uncertainty like "Schrodinger cat" is reflected in the QE of the two particles, in the form of the degree of QE in our model (Wei, 2016).

The figure of 50 per cent of times of iterations $N_{C\max1}$ for the first stage could be considered as a switching point, which switches the calculating method between merging with the effect of QE and conventional PIO. The reason why we use 50 per cent as the switching point, is combining both theoretical assumptions and simulation experiments. Theoretically, by the assumption of initial state $|\psi(0)\rangle = c|01\rangle + d|10\rangle$ for QE, the entanglement degree $\boldsymbol{C}$ will oscillate with attenuation and tend to decrease to a constant value gradually. Given the equations (4) and (5), whether the terminal value equal to zero is determined merely according to the value of the intrinsic decoherence coefficient γ.

However, in the simulation results shown in Figure 4, it turns out to be more complex. Because of the random initial speed of all the virtual "pigeons" and the fitness of boundary coordinates state, the fitness function in the beginning iterations is possible to tend to a low value (even zero), which means the velocity and position may tend to a steady state away from the proper values and get trapped in a local optimum. More details of the switching point illustrations will be shown in the section of simulation results. Considering the degree of QE of both the high impact factor in the early stages of the system and the consistency in the middle-late stages for a more global optimum relatively, we reach the agreement on the switching point at 50 per cent, so that the previous 50 per cent iterations are for QE combining state.

- *Step 4.* Process of the map and compass operator - the second stage.

Figure 2 In the initial state $|\psi(0)\rangle = \sqrt{2}/2|01\rangle + \sqrt{2}/2d|10\rangle$, the evolution at variables of DM (D) and intrinsic decoherence γ

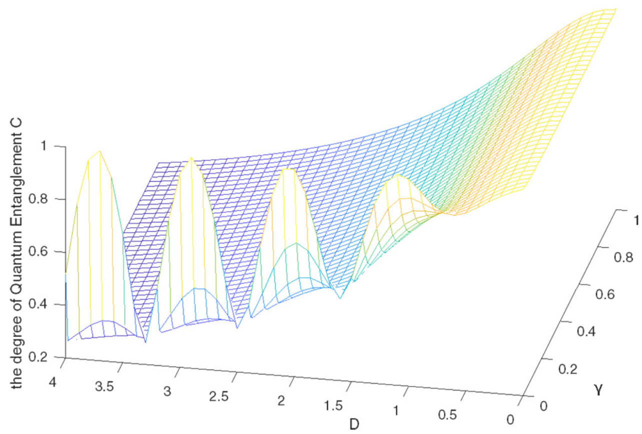
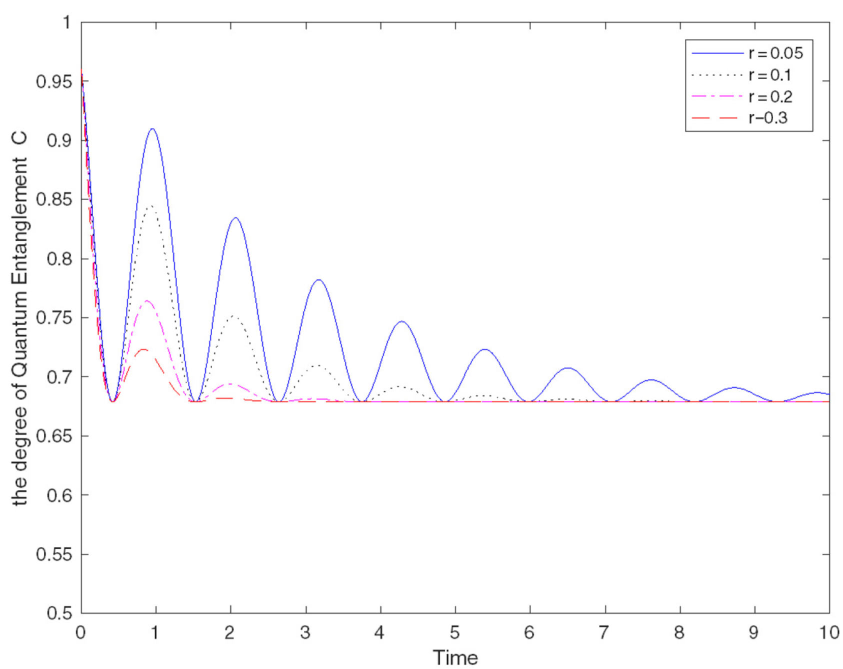


Figure 3 In the initial state $|\psi(0)\rangle = \sqrt{2}/2|01\rangle + \sqrt{2}/2d|10\rangle$, the time-dependent evolution at variable of intrinsic decoherence γ



Note: Figure 3 is under the condition of J = D = 1.0

When the figure of iterations *t* reaches 50 per cent of the proposed iterations N_{Cmax1} in the first operation, the data of each velocity and coordinate position is updated according to the underlying PIO algorithm (which we have mentioned in the 3rd section).

In both Steps 3 and 4, each iteration process will recalculate the fitness of each virtual "pigeon" and obtain the fitness value of the current global optimal point for each iteration, denoted as **result**(**t**), which will be reflected in the simulation curve.

- *Step 5.* Determine whether the current number of iterations *t* is greater than the proposed iterations of map and compass operator N_{Cmax1}. If not, then jump to Step4 and cycle the operation. When it reaches N_{Cmax1} then jump to the next step.

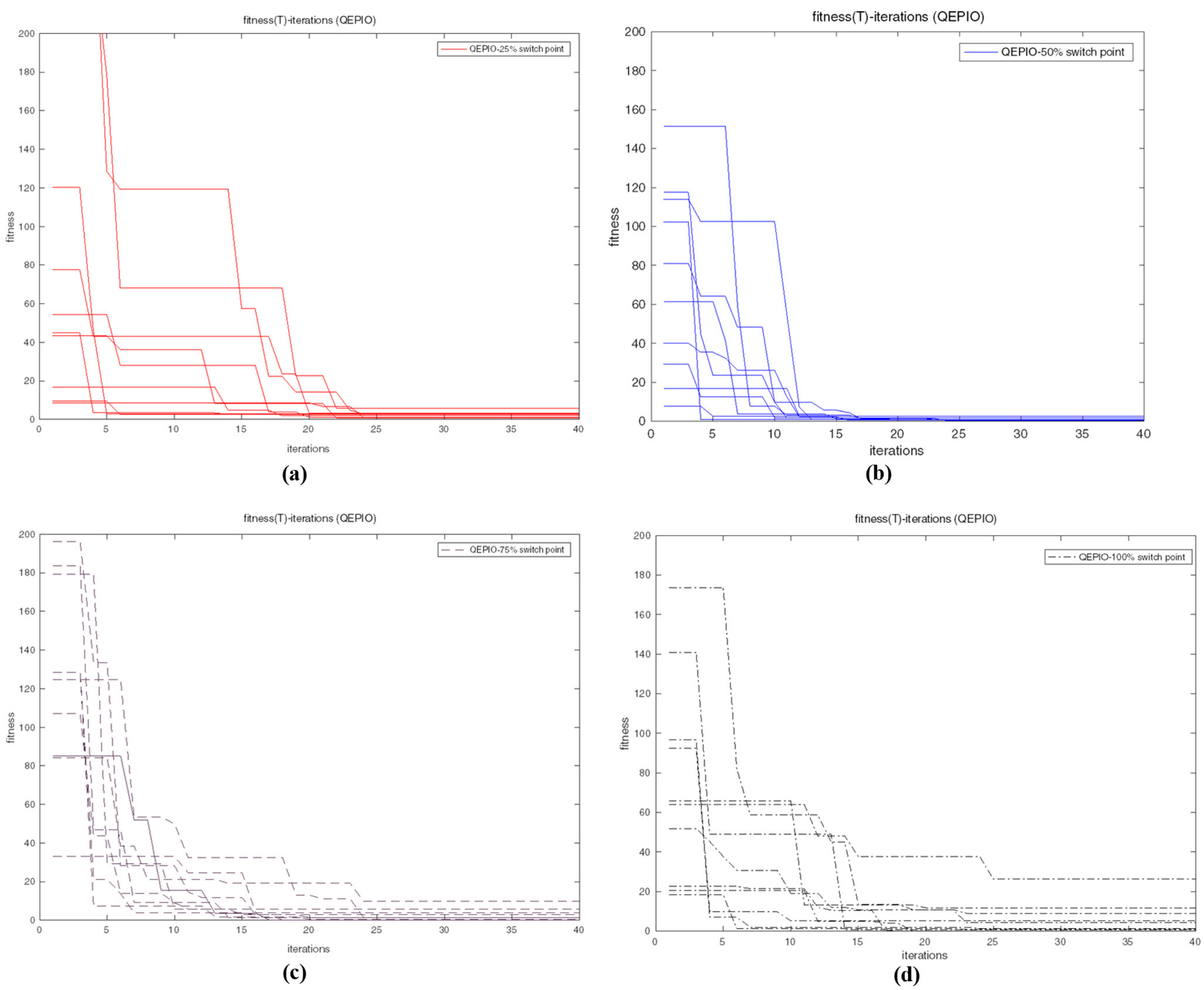
Procedure of landmark operator

- *Step 6.* In this process, the QEPIO algorithm operates according to the basic PIO algorithm. After the fitness calculation, all the virtual "pigeons" will be sorted through the fitness function, "abandon" the half of the "pigeons", and the global best "center" coordinate is obtained according to the formula (8-11), which is the target location of the current iteration. All pigeons will be combined with both their own coordinate components and the vector point to the target location. Then we will make further adjustments to the best direction and location point that can be achieved. Likewise, record the **result**(**t**).
- *Step 7.* Determine whether the current number of iterations *t* is greater than the proposed iterations of landmark operator N_{Cmax2}. If less than N_{Cmax2}, then jump to Step 6 and cycle operation; if it is equal to $N_{Cmax}2$, then go on the next step.

Output

- *Step 8.* Output the **result**(**t**) – *t* in graphical form with point values, and further analyze the data and curve. End the algorithmic process (Figure 1).

Figure 4 The comparison on 10 consecutive results of QEPIO algorithms by different switch points



Notes: (a) QEPIO algorithm by 25 per cent switch point; (b) QEPIO algorithm by 50 per cent switch point; (c) QEPIO algorithm by 75 per cent switch point; (d) QEPIO algorithm by 100 per cent switch point

Simulation results

To investigate the entanglement degree C, switching Point for QEPIO Algorithm and the convergence and robustness of the proposed QEPIO approach, a series of simulations are conducted under several constrained conditions.

Evolution of entanglement degree C

In Figure 2, it bases on the initial entangled state of $\psi(0)\rangle = \sqrt{2}/2|01\rangle + \sqrt{2}/2d|10\rangle$, when the entanglement varies with the intrinsic decoherence factor γ and D. It is shown that when D is a nonzero constant, the increase of γ will lead to the rapid increase on the decay rate of the system entanglement. In other words, the system will tend to zero in a short time, that is, the simulation results of time-independent evolution demonstrate the theoretical derivation process.

From equation (5), we can find that in this initial state, the entanglement degree $\boldsymbol{C}$ of the quantum system is related to the time-dependent evolution of $\boldsymbol{S}$ (and the time $\boldsymbol{t}$is explicit in the S equation), that is, the degree of interaction with the D in the formula has significant relationship with intrinsic decoherence coefficient γ, while unrelated with the applied magnetic field B and the anisotropy parameter Δ. When D is non-zero, the system is oscillating and decreasing with the enhancement of D. Finally, when D increases to a sufficient degree, the entanglement tends to a nonzero steady-state value (as shown in Figure 3). Therefore, by appropriately controlling D, we can obtain the required stable entangled state.

Analysis of switching point for quantum-entanglement pigeon-inspired optimization algorithm

Based on the preliminary analysis of the switching point in the section of QEPIO, in this section, the simulations of different switching points are operated under the same initial parameter settings below. The simulation results could give sufficient support for the switching point selected for 50 per cent in detailed illustrations.

According to the QEPIO model establishment and optimization process, we assume that the number of iterations $N_{C\max1}$ is 25, $N_{C\max2}$ is 15, the total number of virtual "pigeons" N is 30, the dimension D_1 equals to 2, the map and the compass factor R equals to 0.2, and the boundary is [0,100]. In the QEPIO fusion model, we set the intrinsic decoherence coefficient γ = 0.25, the DM interaction vector parameter D_1 = 10, and $\mathcal{J}$ = 1. As we set the target planning point (65,100) in fitness function, we obtain that $fitness\ (x(t)) = (x(i,1)-65)^2 + (x\ (i,2)-100)^2$, that is, through several iterative process to make the terminal value of fitness close to zero.

According to the simulation results of different switching points in Figure 4, it can be concluded that for QEPIO, the 50 per cent of switching point is the relative best choice. In Figure 4(a), when the switching point is 25 percent, the simulation results show that the initial convergence is relatively not good, which is similar to the conventional PIO. When the switching point is 50 percent, shown in Figure 4(b), it indicates a good initial convergence, meanwhile, the final value of fitness function can basically tend to zero. As it can be converted to the conventional PIO when the entanglement influence is almost attenuated. it may be less likely to fall into a local optimum. In Figure 4(c), when the switching point is 75 per cent, it illustrates good initial convergence, but for the reason that the random number plays little role on influence, it is easy to get trapped in a local optimum. More than half of the simulation times cannot result in the consistency of fitness function (for the tendency to zero). In Figure 4(d), the situation for the 100 per cent switching point is even worse, that is, in the map and compass operator, all are replaced by the fusion of QE theory. It can be signified that with an approximate degree of initial convergence compared to 50 and 75 per cent, the results of switching point of 100 per cent is more serious in local optimum issues. Given the conclusions above, we obtain that the switching point of 50 per cent is the proper value relatively, which shows good features of both initial convergence and global optimum.

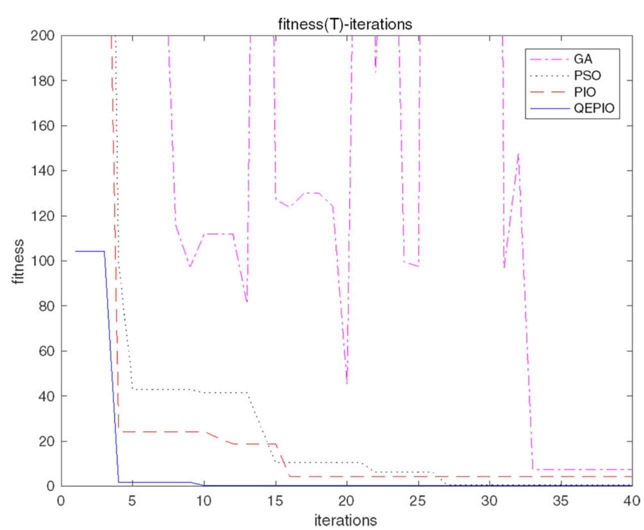
Analysis of convergence velocity for quantum-entanglement pigeon-inspired optimization algorithm

By the analysis for the switching point of the first stage of QEPIO algorithm, we obtain the 50 per cent as the critical point, which will represent the performance for QEPIO in the following explanations. Meanwhile, the settings of initial parameters remain unchanged as the former section.

Figure 5 shows the comparison of QEPIO optimization algorithm with GA, particle swarm algorithm (PSO) and traditional PIO algorithm in convergence velocity, that is, the number of iterations required when the fitness close to zero.

As shown in Figure 5, the curve of QEPIO algorithm in the third times of iterative process has a significant attenuation. After ten times of iterative process, the fitness function closes to the expected value, i.e. 0. Similarly, we can analyze the GA, PSO, PIO algorithm by finding out the iteration points that achieve a large degree of attenuation or almost zero. Compared with GA algorithm, PSO and pigeon-derived algorithms have obvious improvement. Furthermore, the proposed QEPIO algorithm shows more effectiveness than the traditional PIO algorithm (by comparing both the attenuation point and the zero reaching point), so that we can win more time in

Figure 5 Comparison of QEPIO with GA, PSO and PIO Algorithm in convergence velocity



independent navigation and other issues for application, which will be mentioned in the summary.

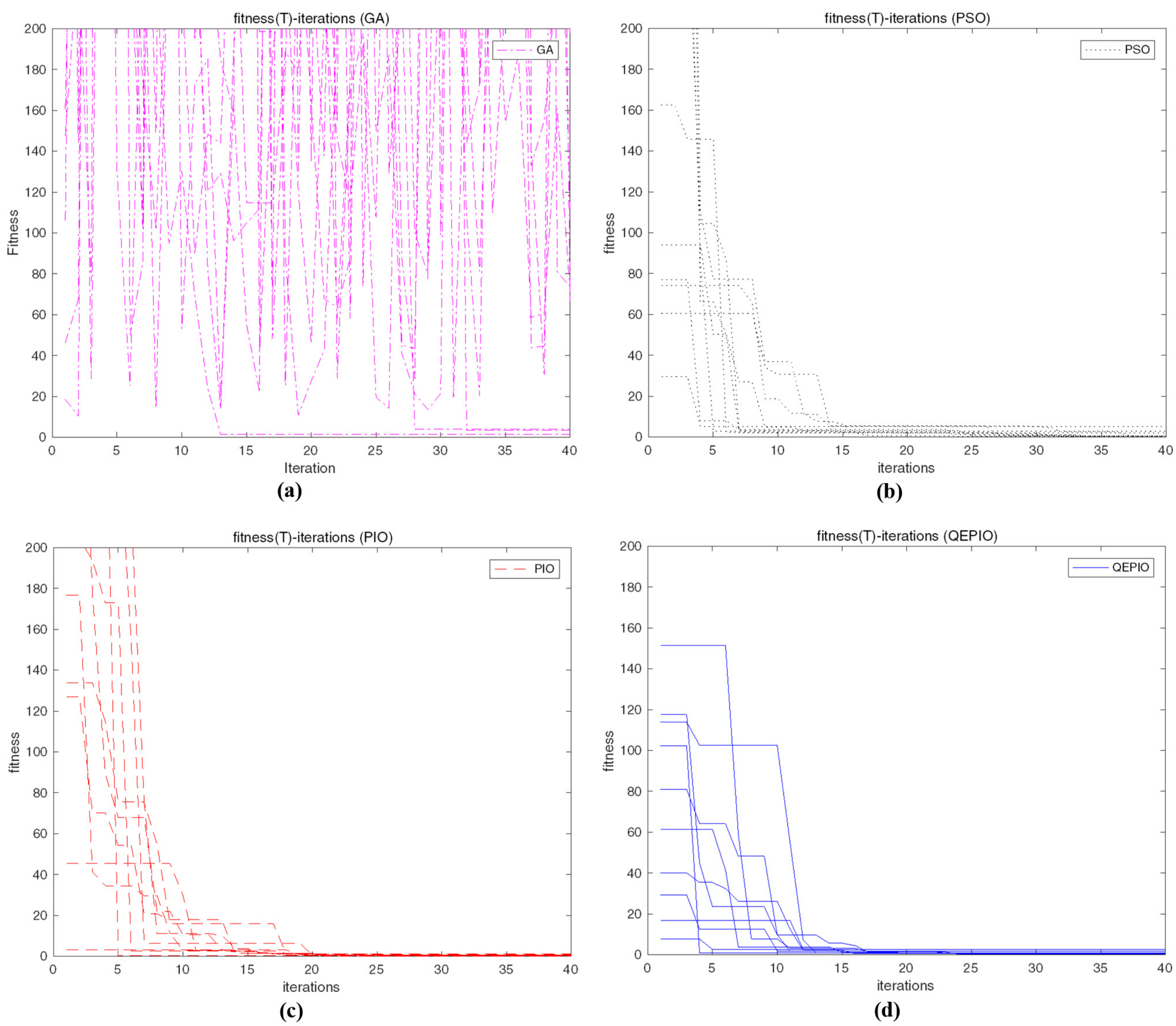
Analysis of robustness for quantum-entanglement pigeon-inspired optimization algorithm

In today's tech development, the total time of operation is extremely important in military applications and other fields. Thus, it is necessary to think over the issue of robustness optimization because of the random initial condition and irresistible disturbance.

The robustness reflected in the following figures [Figure 6 (a), (b), (c) and (d)], fitness - the number of iterations), is an inherent problem of the GA, PSO and PIO-derived algorithms found in the simulation process, in particular, the fitness curves obtained after several successive runs (in our simulation we form 10 consecutive results). Compared with the curves of multiple discontinuities operation, the former is more random, which reflected in the actual results. And it is this point that is not conducive to the autonomous system in an ultra-short time with high-intensity operation.

From Figure 6, we obtain that the robustness of GA algorithm in Figure 6 (a) is relatively poor, and some curves cannot be stabilized after iteration for 40 times. Compared to GA, PSO, basic PIO and QEPIO algorithm in Figure 6 (b), (c) and (d) improve their robustness to great extent. Comparing Figure 6 (b) with (c), the PSO algorithm shown in (b) tends to zero in the range of 5 to 40 times (sometimes more than 40 iterations), which shows the large interval coverage and unstable robust performance, while the PIO algorithm shown in (c) ameliorates the fitness that strictly equals to zero, with the fundamental cause that the PIO algorithm processes the landmark operator at the end of the iteration and further corrects the compass operator. Meanwhile, when Figure 6. (d) is compared with (c), the fitness for QEPIO algorithm of the

Figure 6 The comparison on 10 consecutive results of GA, PSO, PIO and QEPIO algorithms



Notes: (a) GA algorithm; (b) PSO algorithm; (c) PIO algorithm; (d) QEPIO algorithm foremost iterations is advanced shown in (d), and the number of iterations is reduced, on the condition that the steady-state fitness value still approach to zero. The results above manifest the better robustness of QEPIO algorithm.

The QEPIO optimization algorithm proposed in this paper is based on the QE Theory to improve robustness. However, because the various extensions of PIO or PSO hold strong randomness in basic theory, QEPIO algorithm is still not possible to change the absolute robustness of each operation radically. Therefore, we can only make a relative comparison between QEPIO and other extending algorithms, and we will lead to the direction of further research in the conclusion.

Conclusion

In this paper, QEPIO algorithm is proposed for the flight planning issues. We first introduce the QE dynamics theory of the two-particle Heisenberg system XXZ model, and the general idea of the traditional PIO algorithm. Then, we combine the QE of system with basic PIO to devise the QEPIO optimization model, analyze the theoretical and experimental choice of switching point, convergence and complexity and make the logic flow. Eventually, the simulation results manifest that QEPIO has improved the convergence velocity and robustness to some extent, compared to GA, PSO and traditional PIO algorithm.

Meanwhile, there is still room for further research for promoting. First, we assume every UAV as a particle, rather than a specified individual constructed by dynamic model. Factually, flight planning needs to take flight control system model (including three-axis attitude control system, stability and maneuverability, etc.) into account. Second of possible improvements is the robustness of derivative extending algorithms. The improvement of QEPIO algorithm in convergence speed and robustness will be reflected in both breadth and depth of its application. Despite precise guidance in the field of military, there is also a broad prospect in the civil field. For the conditions of special regions impossible for GPS navigation, and the unaffordable price of the whole independent inertial navigation system for ordinary people, quantum communication and navigation will occupy a lot of market space, and QEPIO is proposed for its civil navigation on the research direction.

Furthermore, in this paper, the method of QE merging into basic PIO algorithm is based on the entanglement process between two qubits, which are the QE effect of the coordinates of the current operation and the current global optimal position. If we can discuss the basic problems of PIO in multiple qubits way and make improvements, the map and compass operator parts can be thoroughly modified to the multi-qubit system in the first part of iterations.

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