Interactive Learning Environment for Bio-Inspired Optimization Algorithms for UAV Path Planning

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***Abstract*—This paper describes the development of BOLE, a MATLAB-based interactive learning environment, that facilitates the process of learning bio-inspired optimization algorithms, and that is dedicated exclusively to unmanned aerial vehicle path planning. As a complement to conventional teaching methods, BOLE is designed to help students consolidate the concepts taught in the course and motivate them to explore relevant issues of bio-inspired optimization algorithms through interactive and collaborative learning processes. BOLE differs from other similar tools in that it places greater emphasis on fundamental concepts than on complex mathematical equations. The learning tasks using BOLE can be classified into four steps: introduction, recognition, practice, and collaboration, according to task complexity. It complements traditional classroom teaching, enhancing learning efficiency and facilitating the assessment of student achievement, as verified by its practical application in an undergraduate course "Bio-Inspired Computing." Both objective and subjective measures were evaluated to assess the learning effectiveness.**

***Index Terms*—Ant colony optimization, artificial bee colony, bio-inspired optimization, particle swarm optimization, path planning, unmanned aerial vehicles (UAVs).**

I. Introduction

BY simulating the underlying mechanisms of self-organized behaviors in nature, bio-inspired optimization algorithms have proved to be promising techniques for highly complicated optimization problems [1], [2]. They differ greatly from conventional mathematical methods in that they are developed and implemented by mimicking biological behaviors in nature. Bio-inspired optimization algorithms have drawn great attention from researchers all over the world, as evidenced by the increasing number of conferences, workshops and papers in this field [1]–[3]. Rigorous theoretical analyses have not been conducted for most of the existing bio-inspired optimization algorithms—such as ant colony optimization (ACO), particle swarm optimization (PSO) and artificial bee colony optimization (ABC)—but the superior performance of these algorithms in terms of intrinsic parallelism, self-organization and strong robustness demonstrate broad prospects for future development [4]–[10]. It is thus important for students to have an overall understanding of bio-inspired optimization algorithms, but their complicated principles and equations often make them difficult for students to understand in traditional classroom settings [11].

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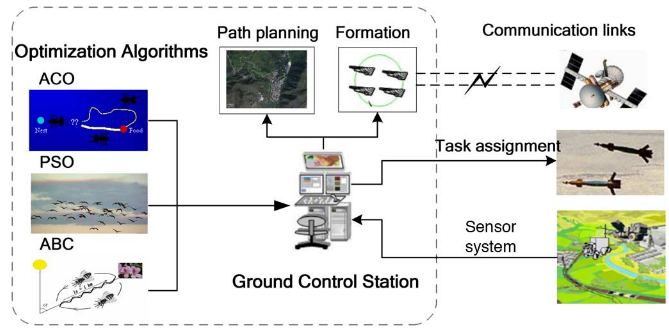

Fig. 1. UAV mission-planning system. BOLE consists of the components inside the dashed box.

Practical implementation activities are thought to play a very important role in learning courses in information science, having a significant effect on learning outcomes and learning efficiency. It has also been shown that abstract results can make a greater effect when illustrated by a graphic presentation rather than by classical mathematical equations [11], [12]. To this end, a bio-inspired optimization learning environment, BOLE, was developed and is described in this paper. This interactive educational tool for unmanned aerial vehicle (UAV) path planning, based on MATLAB graphical user interface (GUI), complements traditional teaching methods. BOLE focuses on solving UAV path-planning problems with three well-known bio-inspired optimization algorithms: ACO, PSO, and ABC. It differs from other tools in that it places greater emphasis on fundamental concepts than on complex mathematical equations.

To motivate active participation, BOLE focuses exclusively on UAV-related matters, far more interesting for new learners than are benchmark functions. More importantly, bio-inspired optimization algorithms are appropriate for many optimization problems in UAV systems, as explained in detail in the following. Research on UAVs has received considerable attention for its attractive potential to perform complicated tasks in remote and hazardous environments [13]–[16]. Path planning, a

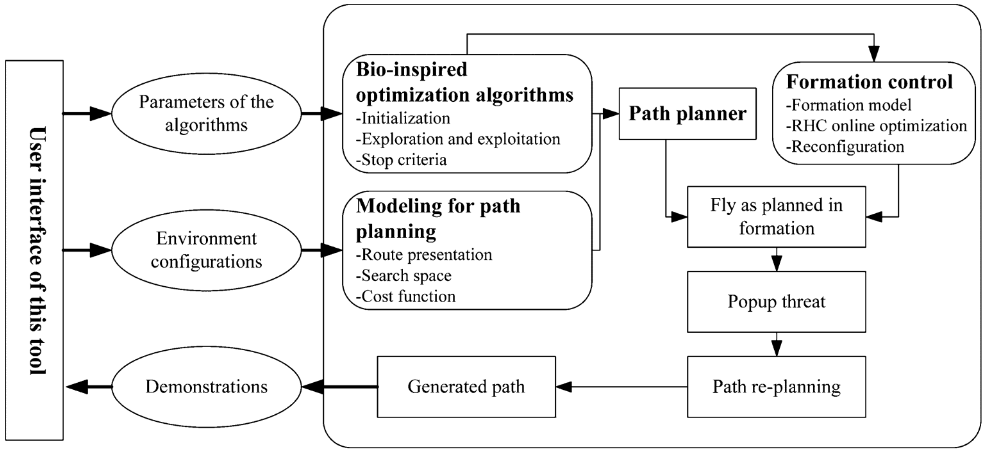

Fig. 2. Architecture of BOLE.

crucial component of the UAV mission-planning system, takes many factors into consideration to find an optimal or near-optimal flight path that connects the launch site and the target site [13]–[19]. Existing approaches for path-planning problems can be classified into three categories: graph-based algorithms, often used in 2-D situations; heuristic search algorithms, of which the most representative is the A* search algorithm; and evolutionary computation algorithms, efficient and robust alternatives that accommodate complicated constraints in path planning. Advantages of choosing bio-inspired optimization algorithms to solve path-planning problems include their strong robustness compared to directed-search approaches, their simplicity of implementation when dealing with complex constraints, their strong adaptability for different scenarios, and their high capability to achieve optimal solutions.

II. Modeling of Path Planning for UAVs

This section describes the architecture of BOLE to provide an overview of this interactive environment. UAV path planning is formulated as a mathematical optimization problem that considers fuel consumption, safety elements and physical constraints to evaluate a candidate route.

A. Architecture of BOLE

The general UAV mission-planning system is shown in Fig. 1.

The architecture of BOLE—the components inside the dashed box in Fig. 1—mainly consists of several modules: modeling for path planning, bio-inspired optimization algorithms, the path planner, the formation controller and the user interface; see Fig. 2.

An effective way to enhance learning is for students to use BOLE to perform path planning for high usability and feasibility. They can easily observe path optimization by implementing the necessary parameters, without having to consider the complicated underlying details.

B. Formulating Path-Planning Problems

Path planning for UAVs can be mathematically described as: given the launching site S and the target site T, and K threat sets $\{T_1, T_2, \ldots, T_K\}$, the objective is to find a set of waypoints $\{W_0, W_1, \ldots, W_n, W_{n+1}\}$ with $W_0 = S$ and $W_{n+1} = T$ [11]–[16]. Each candidate path for optimization can be considered as one individual of the population, and each individual consists of the coordinates of its included path nodes. In this way, path nodes are mapped onto the search space of bio-inspired optimization algorithms. Suppose that there are n path nodes (excluding the start point S and the end point T) in a specified path. Each individual is denoted by a vector with $3n$ elements to represent the spatial information of the path. The position of a path node is composed of three components: the x, y, z coordinates. As a result, the position vector of an individual can be expressed as

$$X_i = (x_{i1}, \ldots, x_{in}, x_{i,n+1}, \ldots, x_{i,2n}, x_{i,2n+1}, \ldots, x_{i,3n})$$

where x_{ij} is the jth dimension of the ith individual's position ($i = 1, \ldots, m$; $j = 1, \ldots, 3n$). The first component of X_i ($x_{i,k}$, for $k = 1, 2, \ldots, n$) represents the abscissa values of the path nodes of the ith path. Similarly, the second ($x_{i,k}$, for $k = n+1, n+2, \ldots, 2n$) and the third component ($x_{i,k}$, for $k = 2n+1, 2n+2, \ldots, 3n$) are the ordinate values and the corresponding flight height of the path nodes, respectively. The solution space of this problem in the 3-D scenario is defined as a cuboid. To speed up the search process, the abscissa values of the population are initialized in the rotating coordinate frame.

C. Objective Function

Accurate modeling of the mission area is closely related to the construction of an objective function for path optimization problems [19]. To obtain a qualified path that minimizes fuel consumption and the probability of exposure to threats, the objective function should be composed of at least two components: the path-length cost and the threat cost. Physical constraints such as the turning angle, the climbing/diving angle, and the flight height are incorporated into the objective function for a specific mission to improve performance. The cost function for a given path can be expressed by

$$J(X_i) = \sum_{k=1}^{5} w_k J_k(X_i) \quad (1)$$

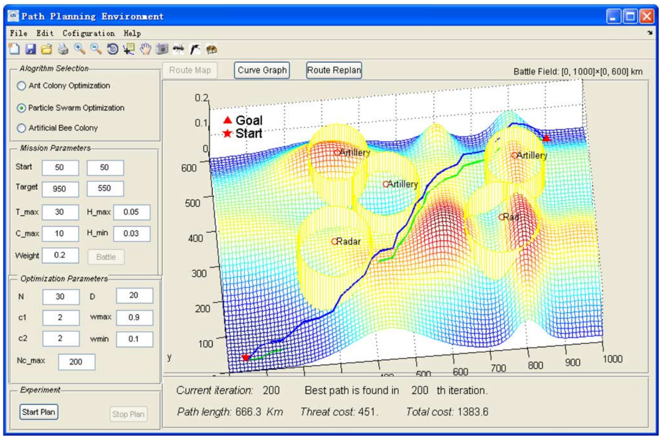

Fig. 3. Results of path planning for UAVs using PSO.

where w_k is the weight coefficient, which is determined by the task type [14]. The path length cost $J_1(X_i)$ is defined as the sum of the absolute value of each segment from the start point to the target point. The threat cost $J_2(X_i)$ is proportional to the sum length of path segments exposed to the threat circles. In order to increase the survival probability, sharp turns and climbs/dives should be avoided to fall within the physical limitations of UAVs. The turn angle cost $J_3(X_i)$ and climb/dive angle cost $J_4(X_i)$ are measured by the differences between the current turning and climbing/diving angle and predetermined maximum turning and climbing/diving angle. The UAV should fly at a low altitude so as to take advantage of the terrain masking effect, but this may increase the risk of crashing. The appropriate altitude thus represents a compromise, the cost of which can be calculated by $J_5(X_i)$.

III. Interactive Learning Processes

This section first details BOLE's configuration procedures and then explains how bio-inspired optimization algorithms are learned through interaction with BOLE. In addition, BOLE's customizable architecture makes it suitable for collaborative activities.

A. Configuration of BOLE

The path-planning interface, Fig. 3, has five main elements: algorithm selection, environment configuration, optimization parameters, the mission area map, and output demonstration.[1] Users can customize the model by setting environmental parameters, and then choose the algorithm to solve the optimization problem from the algorithm selection panel. Once this choice is made the parameter panel will appear, providing students with an intuitive understanding of the algorithm's structure. When all the parameters have been implemented, path planning can be carried out to generate a feasible and optimal path, see Fig. 3. In this environment, tunable parameters include both environmental and algorithm parameters. At the beginning of the learning process, the modification of parameters mainly focuses on algorithm parameters, with students being advised to change only one parameter at a time to avoid confusion.

In the Route Replan section, the predefined path is represented by a dashed line. Users can easily decide where to start the replanning by dragging the slider on the status bar when new threats appear. The path flown by the UAV is marked out with a thick line; the UAV's current position is taken as the start point coordinate for replanning. Clicking the “Execute” option triggers the planning of another efficient path; this newly generated path is shown as a thick black line connecting the replan start point with the target.

B. Interactive Learning

Optimization algorithms' performance is highly dependent on the selection of parameters. A comprehensive understanding of the search process helps a user to develop strategies of parameter settings that enhance an algorithm's efficiency and robustness. In turn, a good understanding of the parameters provides intuitive insight into how optimization works. In this environment, three bio-inspired optimization algorithms, PSO, ACO, ABC, are applied to path planning. In PSO, for example, the role of the inertia weight ω is considered critical for the convergence behavior. Determining the influence of the previous history of velocities on the newly calculated velocity, the parameter ω regulates the tradeoff between the global (wide-ranging) and local (nearby) exploration abilities of the whole population. The effect of the inertia weight can be observed by comparing the evolution of the curves of the generated path for different ω. Fine-tuning of the acceleration coefficients, c_1 and c_2 may result in faster convergence and alleviation of local minima, although they are not critical for the convergence of PSO.

As the tuning parameters are modified, results are shown for each parameter setting, with the newly generated paths being shown on the mission area map; comparing these paths allows students to draw conclusions about parameter selection rules. The best path and the curve evolution for all the particles are also shown in real time, clearly illustrating the convergence characteristics of these algorithms. Additionally, best solutions for each iteration, based on path length, threat cost and total cost [corresponding to the cost in the fitness function in (1)] are also displayed dynamically.

Users can also investigate the stochastic nature of this sort of algorithm by comparing on the terrain map the results of performing the path planning several times, under the same condition and parameters. This makes it possible for students to concentrate on parameter selection, which deepens their understanding of the algorithms. At any time during the evolutionary optimization process an interface screenshot can be saved in JPG format for future analysis, and the generated path coordinates and cost function values can also be saved as “.txt” (or other) files. The feedback provided by these results enables better learning of bio-inspired optimization algorithms and their parameter selection.

C. BOLE as a Natural Support for Collaborative Learning

BOLE was originally designed as an interesting way to introduce students to bio-inspired optimization algorithms and related material. During the teaching process it was discovered that BOLE provides a natural support for collaborative activities because of its customizable architecture, consisting of op-

[1]A copy of this tool is at http://hbduan.buaa.edu.cn/

TABLE I
STUDENT LEARNING ACHIEVED THROUGH BOLE

Stage	Concepts	Skills	Tasks
1	Interactive learning tool, components, functions.	Have an overview of BOLE and know the function of each component.	Describe the perceptual knowledge of this tool and distinguish the function of each part.
2	Recognition, exact functions, implementation.	Be familiar with the rationale behind the algorithms and recognize the exact functions of different modules.	Configure BOLE under given conditions for a specific path-planning mission.
3	Practical extensions, parameters, optimization principle.	Explore how the parameter will affect the population dynamics and analyze BOLE's optimization principle.	Explain the detailed algorithm process and the role each parameter plays in optimization, exploration or exploitation.
4	Customization, improvement, interaction.	Improve BOLE by taking advantage of the customizable architecture or incorporating other techniques.	Team competition for better performance and a more appealing interface; scores depend on the degree of realization.

timization algorithms, environment implementation and visualization elements. Each of these three components can work independently to create a flexible and versatile framework, which means there is a clear separation of these three parts [20]. This feature means BOLE can be used for team-based competitions in which students can interact with the system while collaborating with each other.

An example of this would be for students to modify BOLE by adding innovative features, such as improvements to the optimization algorithms, novel modeling methods or more appealing interfaces. They can also extend the path planning to a more realistic and complicated case, such as coordinated path planning for multiple UAVs. They are welcome to add other popular algorithms, analogous to the three existing ones, to the algorithm library for various applications. Students should review how other groups have made additions and evaluate and comment on their work. This effort may have additional benefits, such as increased engagement, playful learning, or divergent thinking. This work by students will not only improve BOLE but will also significantly enhance their teamwork skills.

IV. Design Activities and Evaluations

A. Student Learning Process

It is natural and reasonable to arrange learning objectives from easy to more complex ones, and by learning stage. The learning tasks can thus be classified into four steps: introduction, recognition, practice, and collaboration (listed by task complexity, see Table I). In the introductory stage, students interact with BOLE, without prior knowledge of the topic area and without a set target. The goal is to show students the broad picture and familiarize them with BOLE's components.

In the recognition stage, conceptual frameworks and theoretical descriptions of bio-inspired optimization algorithms are first explained in the classroom. Having been familiarized with these through mathematical explanations and simple numerical examples, students work with BOLE to understand the algorithms without having to consider complex equations. In the first experimental session, the instructor presents BOLE using an overhead projector, starting with a detailed introduction to its functions and structure and ending with an experimental demonstration. Students are asked to adjust the modeling parameters and the algorithms so as to encourage active participation. In this stage, they are required to recognize the functions of BOLE's various modules and to learn to configure BOLE to carry out a UAV path-planning mission.

In the practice stage, students are free to study the relevant subject-matter content according to their own interests, tastes, and talents, with or without the help of BOLE. They are expected to know the latest advances in this field as reported in recent research papers, and to be able to respond to several open questions by discussing its practical improvements and implementations. They are encouraged to explore, under instruction, how parameters affect the population dynamics. For example, the will examine how convergence curves of cost functions demonstrate the effectiveness of the algorithms. The primary goal of this stage is to endow students with the ability to analyze the optimization principle and make them aware of how to improve the performance of the algorithm.

The next step has students experiment on their own laptops, divided into several groups for a team competition. Each team collaborates to solve any problems they might have and to implement improvements wherever necessary. Any efforts they might make to incorporate other techniques into BOLE are much appreciated. The evaluation criteria for the competition cover two aspects: performance and completeness. Performance is examined by checking the objective value of the generated path for the same settings. Completeness is evaluated by a comprehensive assessment by the teacher and the other student groups. Positive feedback and constructive comments are two further important aspects for evaluation.

After completing the three steps of literature review, parameter investigation and experiment, each team is expected to discuss and compare their results obtained with BOLE. They are expected to have achieved three main learning goals, to understand: 1) how bio-inspired optimization algorithms work to solve optimization problems; 2) parameter selection rules for bio-inspired optimization algorithms; and 3) principles of path planning for UAVs operating in partially known environments.

B. Evaluation

BOLE was introduced in the 2011/2012 offering of the undergraduate-level course “Bio-inspired Computing” (D03D0C09) in the School of Automation Science and Electrical Engineering of Beihang University, China. The course was first offered in the previous academic year (2010/2011). Designed for junior students and lasting the entire academic year, this course is intended to introduce fundamental concepts of bio-inspired optimization algorithms and to equip students to apply this technique to various optimization problems. Both objective and subjective measures were evaluated to assess the effectiveness of BOLE. For the objective measure, all students participating in this study took the same ten-question test, with each question being worth one point; see Table II.

In accordance with the evolution of student learning described above, the test questions were designed to evaluate the skills corresponding to the learning goals, involving fundamental concepts, principles, mathematical formulations, and parameter selection rules. Questions Q1–Q2 examine students' conceptual understanding of algorithms. Then relevant items for the three existing algorithms are investigated, from mathematical descriptions, to theoretical foundations, to performance improvement measures (Q3–Q8). Since the two important aspects of exploration and exploitation can be recognized in population-based algorithms, these could be unified into the same framework, although they have totally different operations. The students are considered to have achieved the predefined learning objective if they are able to design a new optimization algorithm based upon the collective behavior of another natural species (Q9–Q10). Establishing rational evaluation criteria is crucial to ensuring consistency in scoring student answers in-year and between years. These scoring criteria were established after serious discussions with other teachers, trying to cover the essential points of the questions while allow maximum flexibility. Although some of the questions are open-ended and seem somewhat subjective, students need to demonstrate their grasp of the essential knowledge to score the point. For example, students should describe the main operation of their designed algorithm and provide the pseudo-code and a list of the major parameters to get the credit for Q10. Moreover, the test is scored twice by different markers to ensure fair grading.

A statistical analysis of student test results, presented in Table III, reveals that the mean score in the 2011/2012 course was higher than in the previous year. However, it is difficult as yet to draw the conclusion that BOLE is effective in improving the learning ability of students. The t-test statistical method [21] was used to examine this. Choosing a value of .05 for probability p from a typical t-test table yields a critical p-value of 2.06, which is less than the t-test value 4.48. Then the hypothesis that the means of the two sets of data is equal is rejected since the difference between the means is statistically significant. Evidenced by the effect size of 0.88, it is reasonable to argue that the means are statistically different, which indicates the utility of this tool to enhance the learning effectiveness.

For the subjective measure, students' opinion of BOLE and how it contributes to improving their learning process is of significant importance for the instructor [22], [23]. An excellent way to assess the usability of BOLE as well as learning outcomes is to interview the students after they have completed their practice and have been graded. A student survey was administered covering the usability of BOLE and its effectiveness in assisting learning, with each answer being rated on a five-point scale of strongly disagree, disagree, neutral, agree, strongly agree, rated 1–5. The mean survey scores are given in Table IV.

TABLE II
TEST QUESTIONS

No	Questions
Q1	Talk about your understanding of bio-inspired optimization algorithms.
Q2	Please briefly explain the principles of PSO, ACO, and ABC.
Q3	Please write the equations of PSO and explain the effect of each parameter.
Q4	Can you describe the main differences and similarities between PSO and ACO?
Q5	What exactly was the original problem being solved by ACO when it was created?
Q6	What measures can be taken to improve the performance of PSO?
Q7	If the measures you suggested in response to Q6 are implemented, what negative effects might result?
Q8	List the potential applications of bio-inspired optimization algorithms in UAV planning systems.
Q9	Could you design an optimization algorithm based upon the collective behavior of pigeons?
Q10	Give a brief description of your idea in response to Q9.

TABLE III
STATISTICAL ANALYSIS OF STUDENT SCORES

	2010/2011 course	2011/2012 course
mean	6.88	7.72
Standard error	0.188	0.194
Median	6	8
Minimum	4	5
Maximum	8	9
Count	30	30
Standard deviation	0.94	0.97
Sample variance	0.88	0.94

TABLE IV
BOLE STUDENT SURVEY RESULTS

Index	Questions	Score
1	The designed learning path is reasonable.	4.5
2	I enhanced my professional knowledge during the collaborative learning.	4.7
3	BOLE gave me more motivation to learn.	4.2
4	BOLE improved my theoretical knowledge of bio-inspired optimization algorithms and path planning.	4.2
5	I remember the concepts taught better than I would have done had I only had lecture classes.	4.48
6	I would like to explore further with the help of BOLE.	4.16
7	BOLE is easy enough to set up a simulation quickly.	4.3
8	BOLE has a user-friendly interface.	4.04

V. CONCLUSION

This paper has described BOLE, a MATLAB-based interactive educational environment for UAV path planning using bio-inspired optimization algorithms. The student evaluation survey indicates that this environment serves as a suitable complement to traditional teaching methods, as well as being a self-learning tool. It differs from other tools in that it places more emphasis on fundamental concepts than on complex mathematical equations. In BOLE the theoretical background is supplemented with a user-friendly interface that motivates students to learn about bio-inspired optimization algorithms. With its attractive features, BOLE motivates active participation and provides students with an alternative approach to learning bio-inspired optimization algorithms.

Future work will focus on enriching BOLE with more bio-inspired optimization algorithms, such as the newly proposed pigeon-inspired optimization (PIO) algorithm [24].

References

[1] H. Duan and P. Li, *Bio-inspired Computation in Unmanned Aerial Vehicles*. Berlin, Germany: Springer-Verlag, 2014.

[2] E. Bonabeau, M. Dorigo, and G. Theraulaz, "Inspiration for optimization from social insect behaviour," *Nature*, vol. 406, no. 6791, pp. 39–42, 2000.

[3] H. Duan, S. Shao, B. Su, and L. Zhang, "New development thoughts on the bio-inspired intelligence based control for unmanned combat aerial vehicle," *Sci. China Tech. Sci.*, vol. 53, no. 8, pp. 2025–2031, 2010.

[4] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: Optimization by a colony of cooperating agents," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 26, no. 1, pp. 29–41, Jan. 1996.

[5] M. Dorigo, G. D. Caro, and L. M. Gambardella, "Ant algorithms for discrete optimization," *Artif. Life*, vol. 5, no. 2, pp. 137–172, 1999.

[6] M. Clerc and J. Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," *IEEE Trans. Evol. Comput.*, vol. 6, no. 1, pp. 58–73, Nov. 2002.

[7] Kadirkamanathan, K. Selvarajah, and P. J. Fleming, "Stability analysis of the particle dynamics in particle swarm optimizer," *IEEE Trans. Evol. Comput.*, vol. 10, no. 3, pp. 245–255, May 2006.

[8] I. C. Trelea, "The particle swarm optimization algorithm: Convergence analysis and parameter selection," *Inform. Process. Lett.*, vol. 85, no. 6, pp. 317–325, 2003.

[9] D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm," *J. Global Optim.*, vol. 39, no. 3, p. 459, 2007.

[10] C. Xu, H. Duan, and F. Liu, "Chaotic artificial bee colony approach to uninhabited combat air vehicle (UCAV) path planning," *Aerosp. Sci. Technol.*, vol. 14, no. 8, pp. 535–541, 2010.

[11] B. Schneider, P. Jermann, G. Zufferey, and P. Dillenbourg, "Benefits of a tangible interface for collaborative learning and interaction," *IEEE Trans. Learn. Technol.*, vol. 4, no. 3, pp. 222–232, Oct. 2011.

[12] A. M. Howard, P. Chung Hyuk, and S. Remy, "Using haptic and auditory interaction tools to engage students with visual impairments in robot programming activities," *IEEE Trans. Learn. Technol.*, vol. 5, no. 1, pp. 87–95, Mar. 2012.

[13] Y. Fu, M. Ding, and C. Zheng, "Phase angle-encoded and quantum-behaved particle swarm optimization applied to three-dimensional route planning for UAV," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 42, no. 2, pp. 511–526, Feb. 2012.

[14] C. Zheng, L. Li, F. Xu, F. Sun, and M. Ding, "Evolutionary route planner for unmanned air vehicles," *IEEE Trans. Robot.*, vol. 21, no. 4, pp. 609–620, Dec. 2005.

[15] I. K. Nikolos, K. P. Valavanis Nikos, C. Tsourveloudis, and A. N. Kostaras, "Evolutionary algorithm based offline/online path planner for UAV navigation," *IEEE Trans. Syst. Man. Cybern. B, Cybern.*, vol. 33, no. 12, pp. 898–912, Dec. 2003.

[16] P. Li and H. Duan, "Path planning of unmanned aerial vehicle based on improved gravitational search algorithm," *Sci. China Tech. Sci.*, vol. 55, no. 10, pp. 2712–2719, 2012.

[17] P. Bhattacharya and M. L. Gavrilova, "Voronoi diagram in optimal path planning," in *Proc. 4th Int. Symp. Voronoi Diagrams Sci. Eng.*, Glamorgan, U.K., Jul. 2007, pp. 38–47.

[18] P. O. Pettersson and P. Doherty, "Probabilistic roadmap based path planning for an autonomous unmanned helicopter," *J. Intell. Fuzzy Syst.*, vol. 17, no. 4, pp. 395–405, Sep. 2006.

[19] H. Duan, Y. Yu, X. Zhang, and S. Shao, "Three-dimension path planning for UCAV using hybrid meta-heuristic ACO-DE algorithm," *Simul. Model. Pract. Theory*, vol. 18, no. 8, pp. 1104–1115, 2010.

[20] A. Barella, S. Valero, and C. Carrascosa, "JGOMAS: New approach to AI teaching," *IEEE Trans. Educ.*, vol. 52, no. 2, pp. 228–235, May 2009.

[21] D. Carmona Morales, J. E. Jimenez-Hornero, F. Vazquez, and F. Morilla, "Educational tool for optimal controller tuning using evolutionary strategies," *IEEE Trans. Educ.*, vol. 55, no. 1, pp. 48–57, Feb. 2012.

[22] R. Dormido, H. Vargas, N. Duro, J. Sanchez, S. Dormido-Canto, and G. Farias *et al.*, "Development of a web-based control laboratory for automation technicians: The three-tank system," *IEEE Trans. Educ.*, vol. 51, no. 1, pp. 35–44, Feb. 2008.

[23] J. Sanchez, S. Dormido, R. Pastor, and F. Morilla, "A JAVA/MATLAB-based environment for remote control system laboratories: Illustrated with an inverted pendulum," *IEEE Trans. Educ.*, vol. 47, no. 3, pp. 321–329, Aug. 2004.

[24] Pigeon-Inspired Optimization (PIO) Algorithm Accessed, Nov. 2, 2014 [Online]. Available: http://hbduan.buaa.edu.cn/pio/

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