ACSIJ Advances in Computer Science: an International Journal, Vol. 2, Issue 5, No.6 , November 2013
ISSN : 2322-5157
www.ACSIJ.org

# Application of Pre-evolution Genetic Algorithm in Fast Path Planning for UCAV

**Lu Cao[1], An Zhang[2]**

[1] **School of Electronic Information, Northwestern Polytechnical University, Xi'an, 710129, China**
*caolu2563@126.com*

[2] **School of Electronic Information, Northwestern Polytechnical University, Xi'an, 710129, China**
*zhangan@nwpu.edu.cn*

**Abstract**

Due to the complex constraints, more uncertain factors and critical real-time demand of path planning for unmanned combat aerial vehicle (UCAV), an approach of fast path planning based on Voronoi diagram and pre-evolution genetic algorithm (PEGA) is proposed, which makes use of the principle of hierarchical path planning. First the Voronoi diagram is utilized to generate the initial paths and calculate the weight of the paths by considering the constraints. Then the optimal path is searched by using PEGA. Multiprocessors parallel computing techniques are used for PEGA to improve the traditional genetic algorithm and the optimal time is greatly reduced. Simulation results verify that the method of path planning is more favorable in the real-time operation. It can improve the adaptability of dynamic battlefield and unexpected threats for UCAV.

***Keywords:*** *Unmanned Combat Aerial Vehicle, Pre-evolution Genetic Algorithm, Voronoi Diagram, Path Planning, Real-time.*

## 1. Introduction

As one of the core of the mission planning system, path planning is the key for UCAV to achieve autonomous flight and meanwhile is significant to improve the operational effectiveness and penetration ability of UCAV. The key of path planning is to find a flight path to get to the designated area in mission space, which can enable a certain performance index to be optimized on the premise of satisfying the relevant constrains[1]. The main considerations in path planning are the uncertainty and dynamic property of the environment, the real-time performance, effectiveness and optimality of the planning algorithms and the capability to satisfy the constrains of self motion[2]. With the growing complexity of battlefield, for example, using UCAV to attack time-sensitive targets, as a non negligible factor, time has obtained much more attention and fast path planning has become an important approach to improve the environmental adaptability and the survivability of UCAV. The traditional algorithms, such as, the dynamic programming algorithm[3], the Dijkstra algorithm[4], the A* algorithm[5] and so on, need to conduct a comprehensive search of the planning space with their poor parallel computing effect, long computing time and the problem of combination explosion. Intelligent programming algorithms like the simulated annealing algorithm[6], genetic algorithm[7, 8], neural network algorithm[9], ant colony algorithm[10], particle swarm optimization[11] and so on depend on initial conditions. They not only can not adapt to the dynamic change of optimization objectives but also have long run time and they are usually used for off-line optimization.

Based on traditional GA and by utilizing parallel computing technology, pre-evolution genetic algorithm (PEGA) cultivates excellent individuals corresponding to the many possible objective functions during the decision-making period. Once the optimization objective is determined, a fast optimization can be achieved according to the excellent individuals cultivated beforehand and hence GA will have the dynamic performance. It can adapt to the dynamic change of the optimization objective and improve the real-time performance of the fast optimization. Therefore, a PEGA which can make dynamic decisions is proposed and applied in the fast path planning of UCAV. According to the principle of hierarchical path planning, first use the Voronoi diagram to build the battlefield space. Then establish the mathematical model of the UCAV path planning and thus the problem is converted into a function optimization problem. Finally the optimization is made by making use of the dynamism of this algorithm.

## 2. Battlefield Space Based on the Voronoi Diagram

### 2.1 Initial Path Set

The Voronoi diagram is an important geometric structure in computational geometry[12]. The most prominent characteristic of applying Voronoi diagram to path planning is that according to the known distribution of the threat sources in a battlefield, the planning space model can be built and the initial path set can be created. Figure 1 is the Voronoi diagram model of the known threat sources in the battlefield. According to the properties of the Voronoi diagram, the UCAV will gain the supreme security if it flies along the side of the Voronoi diagram. If a new threat point is arbitrarily added to the diagram, it only influences the structure of the Voronoi diagram within the polygon composed by the adjacent threat points. Thus, the Voronoi diagram is applicable to UCAV's local path re-planning under the changeable battlefield environment, for example, the local path re-planning when a threat suddenly appears.

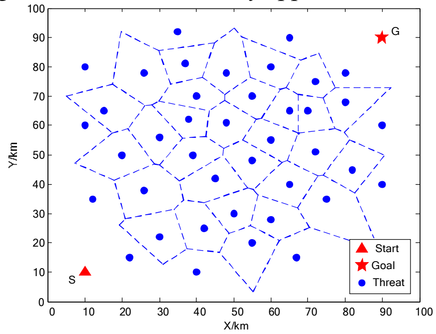


Fig. 1 The Voronoi diagram model of battlefield.

Based on the battlefield Voronoi diagram, the initial path set of UCAV can be denoted as followings: the vertex of the Voronoi diagram is the middle point of the flight path, the side is the path passage and many paths are produced by the combinations of the sides from the start point to the target point. By choosing n paths from these combinations, the initial path set is formed.

### 2.2 Path Cost Calculation

Generally, there are several constraint conditions considered in UCAV's path planning[13, 14]: ①threat factors; ②the path length constraint; ③the maneuverable capability of UCAV; ④the minimum length of the path passage; ⑤ the flight height limit. Hence, the path costs of UCAV in this paper include threat costs $J_{threat}$, fuel costs $J_{fuel}$, the biggest turning angle costs $J_{angle}$ and the shortest path passage costs $J_{length}$. The calculation formulas of these costs are as followings:

$$J_{threat} = \sum_{i=1}^{n} L_i \left(\frac{1}{d_{0.1,i}^4} + \frac{1}{d_{0.3,i}^4} + \frac{1}{d_{0.5,i}^4} + \frac{1}{d_{0.7,i}^4} + \frac{1}{d_{0.9,i}^4}\right) \quad (1)$$

$$J_{fuel} = cL \quad (2)$$

$$J_{angle} = \sum_{i=1}^{k} \left(1 - \frac{a_i^T a_{i+1}}{|a_i||a_{i+1}|} / \cos\alpha\right) \quad (3)$$

$$J_{length} = \sum_{i=1}^{k} \frac{l_{\min} - l_i}{l_{\min}} \quad (4)$$

After considering the four kinds of costs comprehensively, we can obtain the minimum performance index of UCAV's path planning:

$$\min J = k_1 J_{threat} + k_2 J_{fuel} + k_3 J_{angle} + k_4 J_{length} \quad (5)$$

Where $k_1$, $k_2$, $k_3$ and $k_4$ are weighting coefficients and $k_1+k_2+k_3+k_4=1$. The value of these weights depends on the importance and feasibility of the corresponding costs and in this paper they are obtained by applying analytic hierarchy process (AHP).

## 3. Pre-evolution Genetic Algorithm

The design idea of PEGA is using multiprocessor parallel technology[15]. While making decisions in one processor, use another different processor to carry out the advanced evolution for all possible objectives and to cultivate the excellent individuals of every possible optimization objective function. Once the decision is made, there are already excellent individuals within the population which are very close to the optimal solutions corresponding to all the objective functions respectively. On this basis specific objective function optimization can be achieved and this can greatly shorten the searching time, improve the real-time performance and enable GA to adapt to the dynamic change of the optimization objective. PEGA is different from multi-objective evolutionary algorithm (MOEA). MOEA is looking for one better solution for all objectives with the assumption that all objectives have the same optimal solution based on their compromise, while PEGA conducts advanced optimization for all objectives.

According to the above design idea, the key to PEGA is to reserve the excellent individuals of every objective in the process of evolution. If there are $n$ possible objective functions, the individual can be reserved as long as it is good for one particular function. Suppose there are $n$ candidate objective functions, we can choose one as the main objective function according to the prior knowledge, for example, $f_1$ , and then $f_2 \cdots\cdots f_n$ are regarded as the implicit objective functions. Individuals in the current population have their function values corresponding to each objective function and during the evolution of $f_1$ a new individual set can be formed through regular selection, crossover and mutation operation. New individuals have different fitness and function values for each objective function and when using new individuals to replace a part of individuals in the original population, it cannot just consider the fitness of $f_1$ but also the fitness of all other objective functions. So individuals are not good for any objective function should be replaced rather than merely those that are not good for $f_1$. Therefore, a comprehensive fitness function should be set up and it is weighted by each objective function's fitness.

## 4. Path Planning Based on PEGA

The basic framework of path planning based on PEGA includes five parts: path coding, generating initial population, fitness function design, evolutionary operator design and determining the selection mechanism. Among them fitness function design is the key to PEGA. By applying parallel computing technology during the evolution to calculate the value of various cost functions in UCAV's path planning, the comprehensive fitness value can be obtained. Once the battlefield environment changes, the cost functions can be adjusted to form a new comprehensive fitness function to meet the need.

### 4.1 Fitness Function Design

For a single UCAV path, formula (5) can be used as its fitness function, assuming that the minimum value of the threat costs, the fuel costs, the biggest turning angle costs and the shortest path passage costs are the four objective functions, that is,

$$\begin{aligned} f_1 &= \min J_{threat} \\ f_2 &= \min J_{fuel} \\ f_3 &= \min J_{length} \\ f_4 &= \min J_{angle} \end{aligned} \tag{6}$$

In the light of operational experience, avoiding threats should be the primary consideration in UCAV-to-ground attack. Thus, $f_1$ is regarded as the main objective function and $f_2$, $f_3$ and $f_4$ are the implicit objective functions. Finally set up a comprehensive fitness function and it is weighted by each objective function's fitness. The comprehensive fitness function is expressed as,

$$f = k_1 f_1 + k_2 f_2 + k_3 f_3 + k_4 f_4 \tag{7}$$

Where $k_1$, $k_2$, $k_3$ and $k_4$ are weighting coefficients, the same as formula (5). During the evolution, when conducting optimization for $f_1$, individuals that are good for $f_2$, $f_3$ and $f_4$ will be reserved in the population. Cultivate the excellent individuals of every possible objective function and thus once the optimization objective changes, for example, a sudden threat arising, the comprehensive fitness function can be changed by adjusting the weighting coefficients. On the basis of this population, the optimization for the new comprehensive fitness function can quickly converge.

### 4.2 PEGA Flow of Fast Path Search

The flow chart of UCAV's fast path searching based on the Voronoi diagram model and PEGA is shown in figure 2. The searching flow based on PEGA differs from that based on the traditional GA. The determination of fitness functions during the evolution in PEGA is a dynamic process, that is, all individuals optimize the possible objective functions respectively. Then a comprehensive fitness function is proposed and it changes with the change of the battlefield environment, satisfying the restriction of constraints. Whereas in traditional GA, the fitness function is determined at the beginning, when there is a sudden threat, UCAV cannot make adjustments in time and this may cause UCAV losses and even lead to mission failure.

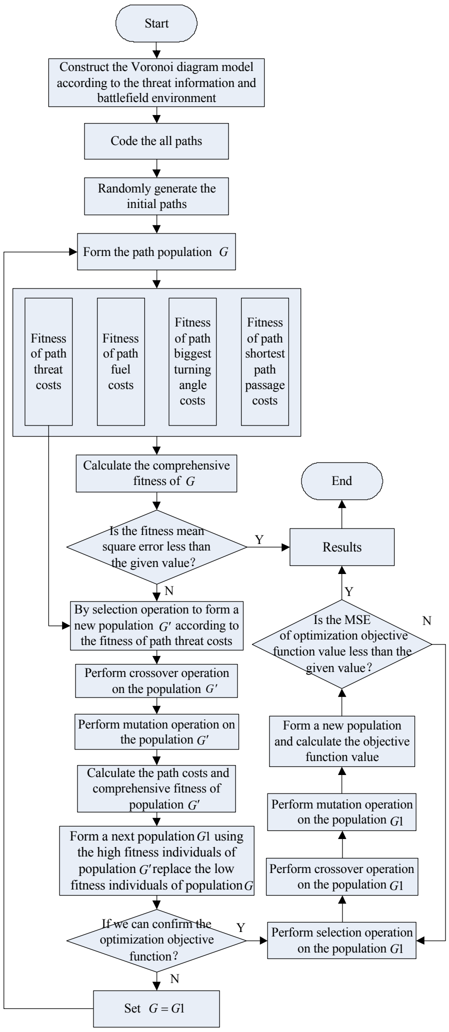


Fig. 2 PEGA flow of fast path search for UCAV.

## 5. Simulation Experiments and Result Analysis

Double thread method is used in simulation, the first thread receives real-time information of the battlefield environment and determines the comprehensive fitness function, while the second thread conducts advanced evolutionary operation and cultivates excellent individuals for path threat costs, fuel costs, biggest turning angle costs and shortest path passage costs. Once the comprehensive fitness function is confirmed, we can get the optimal solution by GA.

(1) Experiment One: the planning results and analysis in static environment

First, the planning effects of PEGA and GA in static environment are studied. In this experiment, all threat sources are set in advance and the threat strength does not change in the process of planning. The parameter settings of GA are the same as those of PEGA. Figure 3 and Figure 4 are the experiment results of the path planning based on PEGA and GA. Figure 3 shows the initial paths and Figure 4 shows the optimal path when the cycle times of the two algorithms are 60 and 61 respectively. We can see from Figure 4 that both two algorithms can search to the optimal path and the planning result is the same, meanwhile the cycle times that need to get the optimal path are basically the same.

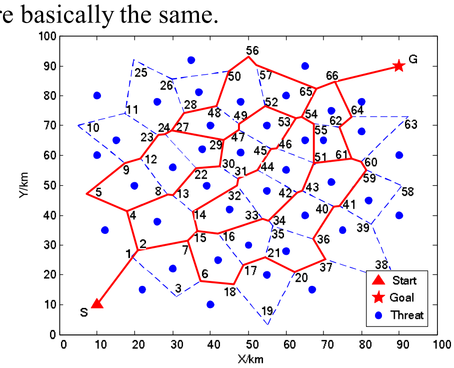


Fig. 3 The initial paths of PEGA and GA.

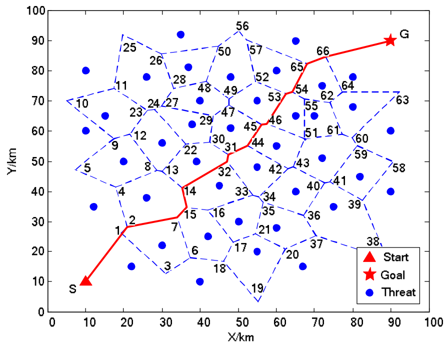


Fig. 4 The optimal path of PEGA and GA.

Figure 5 are the changing curves of the comprehensive fitness along with the changing evolutional generation based on PEGA and GA. From this figure, it can be seen that the changing process of the comprehensive fitness based on PEGA and GA are basically the same. This is because there is no new threat appearing in this experiment, that is, the battlefield environment is stable and thus the comprehensive fitness function is fixed. Therefore, the path planning based on PEGA is equivalent to that based on GA and the calculation process and the planning result of these two algorithms are the same.

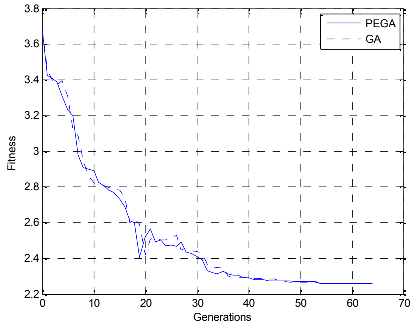


Fig. 5 The fitness curves of PEGA and GA.

(2) Experiment Two: the planning results and analysis when a sudden threat appears.

The results under the condition of emergent threats are analyzed. In this experiment, the threat appears at the coordinates (62, 72) and other parameter settings are the same as those in experiment one. During the planning process, the positions and strengths of the initial threat sources are identical with those in experiment one, so the initial paths is exactly alike Figure 3. Figure 6 shows the path planning results based on PEGA and GA when a sudden threat appears, and the heavy line is the optimal path and the dot within the diamond is the position of the new threat.

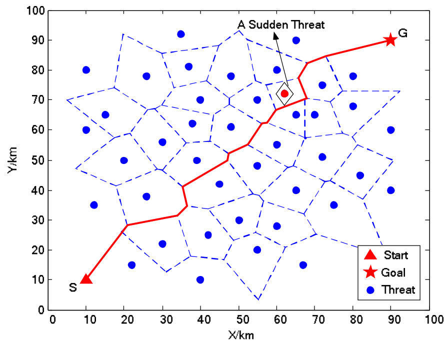


Fig. 6 The optimal path on a Sudden Threat.

From Figure 6, we can see that the planning results of the two algorithms are still the same, but the methods used to deal with the emergent threats during planning process are different. When a sudden threat appears, it will cause the reconstruction of local Voronoi diagram. Since in GA's path searching process, the fitness functions have been determined in advance, only a small part of individuals in the population which is previously produced through genetic evolution can adapt to the change, thereby affecting the final planning results, and the optimal path may not be acquired. Hence, GA needs to regenerate the initial paths and conduct the path searching again, and this will cause vast time consumption. However, in the path planning based on PEGA, the excellent individuals of every possible objective function are reserved in the searching process and when a sudden threat appears, a new comprehensive fitness function can be formed to satisfy the optimization requirement by adjusting the weighting coefficients of all possible objective functions. Figure 7 shows the changing curves of the comprehensive fitness along with the changing evolutionary generation.

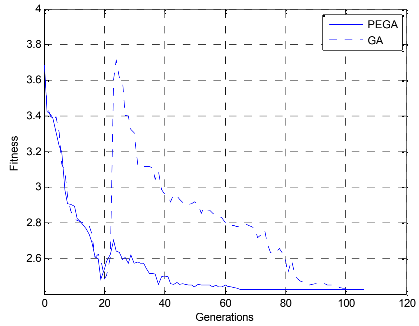


Fig. 7 The fitness curves on a Sudden Threat.

It can be seen from Figure 7 that before the threat emerges, the calculation process of the two algorithms is similar and the change trend of the comprehensive fitness stays the same. In generation 22, a sudden threat appears and in the path planning based on PEGA, the comprehensive fitness function is adjusted and the optimal path is searched in generation 67. The total evolutionary generations are basically the same as experiment one. It is obvious that sudden threats do not have much impact on the path planning based on PEGA. However, the traditional GA needs to regenerate the initial paths and conduct the path searching again, meanwhile the comprehensive fitness changes drastically, finally the optimal path is searched after a further 83 generations. The total evolutionary generations and the consuming time of traditional GA increase, compared with those of the path planning based on PEGA. Due to the unpredictable sudden threat, the path planning algorithm must be able to update the environment information quickly but also get a fairly satisfactory planning result in specified time. The path planning based on PEGA can satisfy the changing battlefield environment by adjusting the comprehensive fitness function and this improves the speed of path searching.

## 6. Conclusions

In this paper, according to the idea of hierarchical path planning, the pre-evolution genetic algorithm is applied in fast path planning of UCAV. With deep analysis of the UCAV's path planning constraints and battlefield environment, the path planning model based on Voronoi diagram is established by utilizing the topological properties of Voronoi diagram. In the meantime, when calculating the path costs, the threat costs, the fuel costs, the biggest turning angle costs and the shortest path passage costs are comprehensively considered. The pre-evolution genetic algorithm improves the traditional GA by applying the pre-evolution strategy, that is, by using the multiprocessor parallel computing technology, cultivates excellent individuals of every possible objective function in the determination process of the optimization function and conducts a fast optimization once the optimization objective is determined, so it can be used under the condition when the objective functions are dynamically decided. Therefore, this method used in path planning of UCAV can ensure the real-time performance and develop an evolution during which the optimization objective changes along with the battlefield environment and a following fast optimization can be achieved.

**Acknowledgments**

In this paper, the research is supported by the Aviation Science Foundation of China under Grant No. 2011ZC53026.

## References

[1] Y. Y. Wang, T. T. Wei, X. J. Qu, "Study of Multi-objective Fuzzy Optimization for Path Planning", Chinese Journal of Aeronautics, No. 25, 2012, pp. 51-56.
[2] Y. Chen, X. G. Zhao, J. D. Han, "Review of 3D Path Planning Methods for Mobile Robot", Robot, Vol. 32, No. 4, 2010, pp. 568-576.
[3] A. Chaudhry, K. Misovec, R. D'Andrea, "Low Observability Path Planning for An Unmanned Air Vehicle Using Mixed Integer Linear Programming", The 43rd IEEE Conference on Decision and Control, 2004, Vol. 4, pp. 3823-3829.
[4] J. N. Amin, J. D. Boskovic, R. K. Mehra, "A Fast and Efficient Approach to Path Planning for Unmanned Vehicles", AIAA Guidance, Navigation and Control Conference, 2006, AIAA 2006-6103.
[5] R. Kala, A. Shukla, R. Tiwari, "Fusion of probabilistic A* algorithm and fuzzy inference system for robotic path planning", Artificial Intelligence Review, Vol. 33, No. 4, 2010, pp. 307-327.
[6] R. S. Tavares, T. C. Martins, M. S. G. Tsuzuki, "Simulated Annealing with Adaptive Neighborhood: A Case Study in Off-line Robot Path Planning", Expert Systems with Applications, Vol. 38, No. 4, 2011, pp. 2951-2965.
[7] K. H. Sedighi, K. Ashenayi, T. W. Manikas, "Autonomous Local Path-Planning for A Mobile Robot Using A Genetic Algorithm", IEEE Congress on Evolutionary Computation, Portland, 2004, Vol. 2, pp. 1338-1345.
[8] M. Tarokh, "Genetic Path Planning with Fuzzy Logic Adaptation for Rovers Traversing Rough Terrin", Studies in Fuzziness and Soft Computing, 2007, Vol. 208, pp. 215-228.
[9] L. Howard, X. Y. Simon, B. Yevgen, "Neural Network Based Path Planning for A Multi-Robot System with Moving Obstacles", The 4th IEEE Conference on Automation Science and Engineering, 2008, pp. 163-168.
[10]M. Chen, Q. X. Wu, C. H. Jiang, "A modify ant optimization algorithm for path planning of UCAV", Applied Soft Computing Journal, Vol. 8, No. 4, 2008, pp. 1712-1718.
[11]J. L. Foo, J. S. Knutzon, J. H. Oliver, "Three-Dimensional Multi-Objective Path Planning of Unmanned Aerial Vehicles Using Particle Swarm Optimization", The 48th AIAA/ASME /ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, 2007, AIAA 2007-1881.
[12]M. de Berg, O. Cheong, M. van Kreveld, Computational Geometry - Algorithms and Applications(Third Edition), Berlin: Springer-Verlag, 2008.
[13]C. W. Zheng, M. Y. Ding, C. P. Zhou, "Real-time Route Planning for Unmanned Air Vehicle with An Evolutionary Algorithm", International Journal of Pattern Recognition and Artificial Intelligence, Vol. 17, No. 1, 2003, pp. 63-81.
[14]P. Yan, M. Y. Ding, C. W. Zheng, "Coordinated Route Planning via Nash Equilibrium and Evolutionary Computation", Chinese Journal of Aeronautics, Vol. 19, No.1, 2006, pp. 18-23.
[15]J. G. Shi, X. G. Gao, X. M. Li, "Study on Pre-evolution Genetic Algorithm", Journal of Astronautics, Vol. 26, No. 2, 2005, pp. 168-173.

**Lu Cao** is a post-doctor. His main research interest is aviation weapon System technology.

**An Zhang** is a doctoral tutor in NPU. His main research interests are aviation weapon system technology, complex system modeling, simulation and effectiveness evaluation.