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A Genetic-Algorithm-Based Approach to UAV Path Planning Problem

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Abstract: - This paper presents a genetic-algorithm-based approach to the problem of UAV path planning in dynamic environments. Variable-length chromosomes and their genes have been used for encoding the problem. We model the vehicle path as a sequence of speed and heading transitions occurring at discrete times, and this model specifically contains the vehicle dynamic constraints in the generation of trial solutions. Simulation studies have shown that the proposed algorithm is effective in finding a near-optimal obstacle-free path in a dynamically changing environment, and the algorithm can guarantee that all candidate solutions lie within a feasible and reachable path space.

Key-Words: - UAV, Path planning, Genetic algorithm, Dynamic environments, Variable-length chromosomes

1 Introduction

Flight path planning is part of Uninhabited Air Vehicle (UAV) mission planning, and has received considerable research attention [1] [2] [3]. In essence, flight path planning is ultimately responsible for the generation of a trajectory in space which, when followed, maximizes the likelihood of the UAV completing its assigned tasks. However, most previous approaches have their drawbacks. In [2], for example, the planning result needs to be optimized further to make it flyable to UAV. In this paper, we propose an algorithm that can overcome this drawback and can plan flight path effectively.

In this paper a Genetic Algorithm (GA) has been developed and used for the UAV path planning in a dynamic environment. Firstly, an initial set of path genotype strings will be generated randomly, and the elements of the set are variable-length chromosomes. We model the vehicle path as a sequence of speed and heading transitions occurring at discrete times, and this model specifically contains the vehicle dynamic constraints in the generation of trial solutions. Subsequently, a new set of path genotype strings will be generated by genetic operating, some of which will replace the previous strings based on fitness selection. This process is repeated until some predefined stopping criteria are met.

2 Genetic Algorithm

Genetic algorithm is a probabilistic search algorithm, which is motivated by the principles of evolution by natural selection, and can be used for searching effectively for optimal structures from a number of candidate patterns [4].

An implementation of a genetic algorithm begins with a population of chromosomes (typically randomly selected). One then evaluates these structures and allocates reproductive opportunities in such a way that chromosomes that potentially provide a better solution to the target problem are given more chances to "reproduce" themselves than those that potentially lead to poorer solutions. The "goodness" of a solution is typically defined with respect to the current population [4].

3 UAV Path Planning

Path planning is ultimately responsible for the generation of a trajectory in space which, when followed, maximizes the likelihood of the UAV completing its assigned tasks. Without loss of generality, the path planning problem considered in this paper can be described as follows.

Given:

A UAV, initially at location (x_0, y_0);

A target to be reached, located at (x_T, y_T);

A set of obstacles, located at (x_i^o, y_i^o), $i = \{1, 2, ..., N^o\}$ respectively, to be avoided;

To find:

A trajectory for the UAV (x^j, y^j) = $\{(x_k, y_k)\}$ defined at times $k = \{1, 2, ..., N\}$, which arrives at the target. This is equivalent to optimizing a cost function $J(x^j, y^j)$, subject to a set of constraints $g(x^j, y^j) = 0$.

Usually, the cost function $J(x^j, y^j)$ is a weighted scalar function, which must reflect all the forces that conspire to derail the intensions of the UAV.

In this paper, the cost function consists of several components including distance cost, obstacle cost and path length cost.

3.1 Distance cost $J_{distance}$

The distance cost is defined as the distance from the terminal point on a path for the UAV to its goal location. The termination time at the goal location, t_{N^j} is a free parameter, as in this paper we use variable-length chromosome to present flight path. The computation of $J_{distance}$ is straightforward. We define the $J_{distance}$ as the Euclidean distance between the final point on a given trajectory and the target location:

$$J_{distance} = R(\vec{x}^{i,j}[t_{N^j}], \vec{T}^i[t_{N^j}]) \qquad (1)$$

3.2 Obstacle cost $J_{obstacle}$

For the purposes of this research, it is assumed that obstacles in the environment can be appropriately approximated by circle (This is for a 2-dimensional case). Thus, each obstacle is defined by its time-varying center position and diameter of the circle. We model UAV as a disk of radius, R_{UAV}, and consider its motion along a particular path segment from time t_k to t_{k+1}, as shown in Figure 1. So the $J_{obstacle}$ is computed by collision detection.

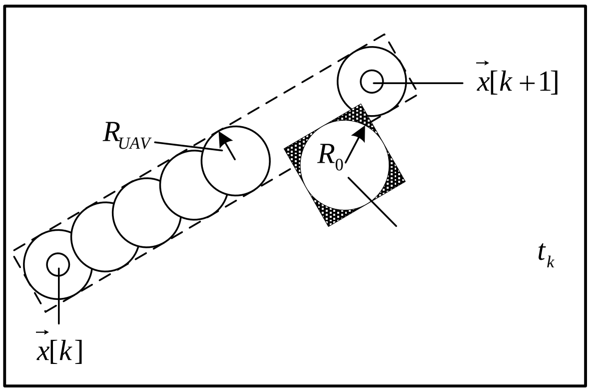


Fig. 1. obstacle cost calculating

An appropriate collision detection scheme would model the motion of both the UAV and obstacles, using bounding rectangles to capture their movement over each sample interval. Collision detection would then involve checking for the intersection of each possible pair of rectangles, and calculating the intersection areas between the UAV path bounding rectangle and obstacle bounding rectangles at each sample interval. The obstacle cost $J_{obstacle}$ is equal to the sum of all intersection areas.

3.3 Path Length cost J_{length}

The path length cost is used for the planner to find out shorter paths. The first and most obvious choice is to try and limit the number of points in the path. More specifically, one can try to minimize the J_{length}, which can be expressed as:

$$J_{length} = \sum_{k=0}^{N^j-1} u_k \cdot (t_{k+1} - t_k) \qquad (2)$$

Where u_k is the UAV velocity from time t_k to t_{k+1}. N^j is the number of the sample intervals.

4 Proposed GA for UAV Path Planning

This section discusses the proposed path planning algorithm, including genetic representation, chromosome decoding, the choice of fitness function, and GA operators.

4.1 Genetic Representation

In the presented algorithm, a chromosome consists of different sequences of positive integers that represent a sequence of speed and heading transitions taking place at discrete times {t_k, k= 0, 1... N} respectively. The possible transitions, assumed to be triggered at the start of each interval tk is thus one of the following.

Table 1. Genetic representation

Parameter	Genetic representation								
	1	2	3	4	5	6	7	8	9
Δu	+	-	0	-	0	+	0	+	-
$\Delta \varphi$	-	-	-	0	0	0	+	+	+

where Δu and $\Delta \varphi$ denote increment in velocity and heading of the UAV, respectively. Note that the ordering of the transitions in Table 1 is arbitrary and the transitions mean that all turns can be done at the maximum turn rate $\dot{\varphi}_{\max}$ and all accelerations/decelerations can be done at the maximum value $a_{\max}$. This corresponds to an aggressive maneuvering of the UAV.

Thus, the j^{th} individual of a population can be expressed as a sequence of transitions that reflect the nature of changes in the motion state to be initiated at time instant k^{th} :

$$\vec{P}^j = [I_1 \; I_2 \; ... \; I_\ell] \tag{3}$$

where I_k indicates the type of change to be initiated at sampling interval k^{th}, and ranges from 1 to 9 in our case.

4.2 Chromosome Decoding

Given a sequence of transitions in speed and heading as discussed above, it is then necessary to generate a corresponding expected trajectory for the flight. This trajectory is typically required for evaluation of the performance of a trial solution. In the case of 2-dimensional space, given a constant acceleration and turn rate as defined by the transition rules in Table 1, the motion of the UAV over an interval is described by the equations:

$$\begin{aligned} u[k+1] &= u[k] + \Delta u \\ \varphi[k+1] &= \varphi[k] + \Delta\varphi \\ x[k+1] &= x[k] + u[k+1]\cos(\varphi[k+1]) \\ y[k+1] &= y[k] + u[k+1]\sin(\varphi[k+1]) \end{aligned} \tag{4}$$

where u is UAV velocity with $u_{\min} \le u \le u_{\max}$, φ is the UAV heading with $|\varphi| \le \varphi_{\max}$, Δu and $\Delta \varphi$ are the inputs, and (x, y) are inertial UAV position coordinates.

The rationale for using the kinematics model is based on the assumption that there exist inner and outer loop navigation control laws, which enable the UAV to track a trajectory as long as changes in speed and heading are within the UAV's motion limits.

4.3 Fitness Function

The fitness function interprets a chromosome in terms of physical representation, and evaluates its fitness based on desired traits of the solution. And, the fitness function must accurately measure the quality of the chromosomes in the population. The fitness function in the UAV path planning problem evaluates the cost of a given path. Therefore, the fitness function is defined as follows:

$$f^j = \frac{1}{\sum_{i=1}^{n} \omega_i J_i(x^j, y^j)} \tag{5}$$

where (x^j, y^j) represents the j^{th} trajectory, f^j is the fitness value of the trajectory, $J_i(x^j, y^j)$ represents the i^{th} cost component of the trajectory, $\vec{\omega} \in \Re^n$ is a weight vector relating to each component of the cost, and n is the total number of the components, in this paper, n =3. The components of the cost include $J_{distance}$, $J_{obstacle}$ and J_{length} .

The fitness function of GA is generally an objective function that needs to be optimized. The fitness function (5) has a lower value if the fitness characteristics of a chromosome are better than others. In addition, the fitness function introduces a criterion for the selection of chromosomes.

4.4 Genetic Operators

4.4.1 Selection

The selection (reproduction) operator is intended to improve the average quality of the population by giving the high-quality chromosomes a better chance to get copied into the next generation. Proportionate selection is used in our paper.

4.4.2 Crossover

The mechanism of the crossover is the same as that of the conventional one-point crossover [4]. Fig. 2 shows an example of the crossover procedure.

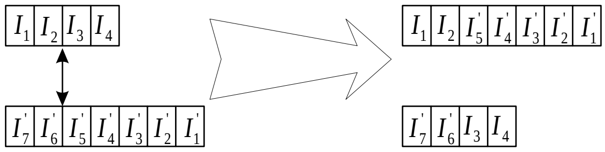


Fig. 2. Example of the crossover procedure

4.4.3 Mutation

The population undergoes mutation by an actual change or flipping of one of the genes of the candidate chromosomes, thereby keeping away from local optima.

```
/*C : Input chromosome, C* : Output chromosome*/
s_m = choose_rand(C); // Randomly choose a node as a mutation poin
C[s_m] = Random(1,9); // Randomly change the value of the node
C* = C;
```

Fig. 3. Pseudo-code of the mutation [5]

site

4.4.4 Insertion and Deletion

The insertion and deletion operators implemen variable-length chromosomes. The insertion operator inserts a gene into the candidate chromosome. Fig. 4 shows an example of the insertion procedure. The deletion operator deletes a gene from the candidate chromosome. Fig. 5 shows an example of the deletion procedure.

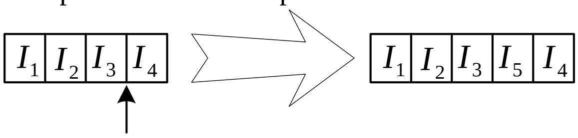


Fig. 4. Example of the insertion procedure

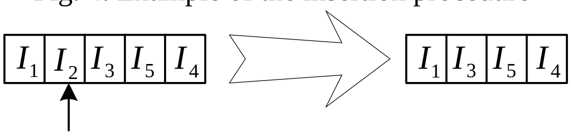


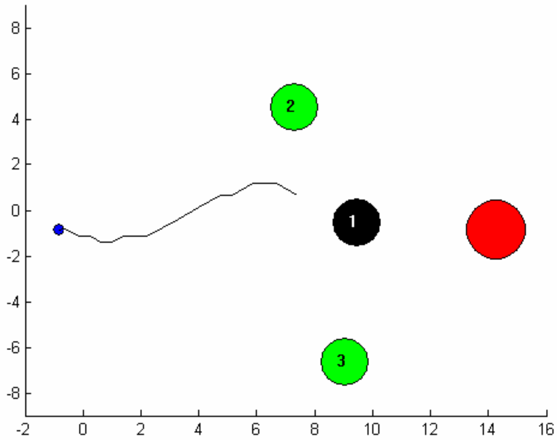
Fig. 5. Example of the deletion procedure

5 Experimental Results

In this section, some results of path planning experiments in dynamic environments are presented using the proposed algorithm.

The UAV is assumed initially at (x_0, y_0) = (0, -1) with speed $u[0]=2$ and heading $\varphi[0]=0$. Speed changes are limited to 1 with the UAV speed constrained to be an integer in the range [1, 3]. Changes in heading are limited to $\pm 30^0$. The environment through which the UAV must navigate contains three obstacles ($N^o = 3$) located at the positions as shown in Figure 6. A target is located at (x^T, y^T) = (14, -1). In this example, the obstacle "2" is moving obstacle.

Figures 6(a)-(c) show the planning result by the presented genetic algorithm, where an assumption has been made that the movement of the moving obstacles are predictable by assessing its position at any point in time.



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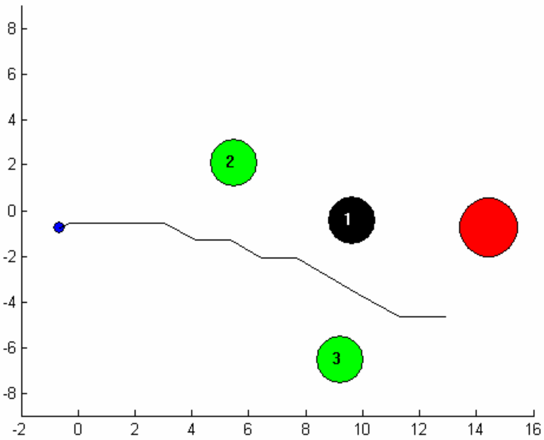
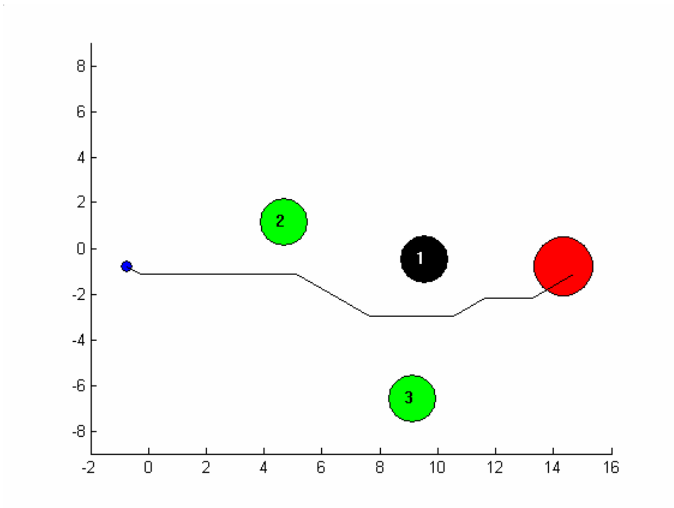
(a)



(b)



(c)

Fig. 6. Path planning in dynamic environment

6 Conclusion

This paper presented a genetic algorithm for solving the UAV path planning problem. The algorithm can search the solution space in a very effective manner. Simulation studies show that the algorithm is effective in finding near-optimal, obstacles-free paths in a dynamically changing environment.

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