RESEARCH ARTICLE

PRELIMINARY DESIGN OF ONBOARD GUIDANCE SYSTEM USING DYNAMICALLY DISTRIBUTED GENETIC ALGORITHM FOR EXPERIMENTAL WINGED ROCKET.

Masatomo Ichige, Koichi Yonemoto and Takahiro Fujikawa.
Department of Mechanical and Control Engineering, Kyushu Institute of Technology, Japan.

Abstract

The authors have been developing the guidance system of winged rocket using dynamically distributed genetic algorithm (DynDGA) for trajectory optimization. DynDGA is an advanced genetic algorithm (GA) which can enhance the variety of trajectories and maintain the trajectory search performance. However, DynDGA requires higher computing power. One of the simple solutions for this problem is to reduce the number of individuals and generations, but it also degrades the solution search capability. For the implementation, authors need to make a tradeoff between these problems. Evolutionary algorithms (EAs) have proven successful in a vast number of static applications and the number of papers produced in this area is growing rapidly. However, they also seem to be particularly suitable for dynamic and stochastic optimization problems such as natural selection. The authors performed some simulations, and the results succeeded to reach the target point. However, at some initial conditions, the simulation could not reach near the target point. This paper describes the simulation results of DynDGA onboard guidance system for experimental winged rocket in dynamic environment.

Introduction:

The Reusable Launch Vehicle (RLV) aimed at the low-cost space transportation system is an idea, which has been planned for more than half a century. However, RLVs have not been realized except the U.S. space shuttle, which has accomplished partial reuse. Kyushu Institute of Technology has been developing winged fully reusable space transportation system (as in Figure 1) and studying autonomous guidance/control algorithm, composite fuel tank and aerodynamic design problems of RLVs ¹. Real-time guidance is one of the challenging tasks because the system needs to generate an optimized guided trajectory even under abort flight. The objective of this study is to develop an algorithm to generate optimal trajectory without any pre-determined trajectory under any uncertainties.
The authors have been developing the guidance system using dynamically distributed genetic algorithm (DynDGA) for trajectory optimization. DynDGA is an advanced genetic algorithm (GA) which can enhance the variety of trajectories and maintain the trajectory search performance. The advantage of adapting DynDGA is obtaining non-divergent solutions, compared with conventional studies such as SQP methods and numerical methods. From the past studies, the basic algorithm for guidance using DynDGA has been developed. As a next step, the authors have been developing the guidance system for real-time implementation. This paper describes the simulation results of DynDGA onboard guidance system for experimental winged rocket in dynamic environment.

Dynamically Distributed Genetic Algorithm:-

GA is a search heuristic algorithm that imitates the process of natural selection. Figure 2 shows the flowchart of GA. At first, GA creates an initial individual group and calculates their fitness. Fitness is the measure of how well the individual is fitted to the conditions. Next, the GA selects two individuals and their crossover is performed. Finally, GA calculates the individuals’ fitness which are generated by the crossover, and selects the individuals that survive to the next generation. Mutation is a process to change the gene values at random with a rate. It makes to escape from the local solution. This procedure is repeated many times, and the optimal result is obtained.

An important feature of this search methodology is the diversity of individuals. In a normal search for an optimal solution, searching is fallen into a local solution. In this situation, escape from the local solution may be achieved by using mutation or the distributed genetic algorithm (DGA). Figure 3 shows the schematic illustration of the DGA model. Using DGA, Individuals are divided into sets of populations called islands, the search of an optimal solution is conducted in each island independently. For every generation, the DGA trades individuals between islands, which is called migration. This process makes it possible to maintain the variation of individuals and to enhance the search performance.
DynDGA is an extension to DGA. Figure 3 shows the model of DynDGA. In DynDGA, the population is distributed into islands based on their dissimilarity, and the number of islands changes dynamically as the optimization proceeds. Hierarchic clustering method is employed to distribute the population into islands. The calculation of the dissimilarity is done using the combinatorial method. Among several approaches, the Ward’s method is used in this simulation. As a result of dynamic clustering, some similar islands are merged, and an island is divided into several islands if necessary. By repeating these procedures, some optimized flight trajectories are finally obtained in each island.

Onboard Guidance System:

Winged rocket model

Kyushu Institute of Technology has been developing reusable space transportation system called WIRES (Winged REusable Sounding rocket, as in Figure 4) since 2005. The objective of this vehicle is to reach 100km altitude and realize the sub-orbital space travel. In the return phase, this rocket glides to a target point using a fully autonomous guidance system based on DynDGA trajectory optimization.

In this simulation, the rocket model is a subscale experimental winged rocket called “WIRES#015”. The mission objective of this vehicle is to evaluate the real-time optimal trajectory generation using DynDGA, demonstrate the LOX-Methane propulsion system, reentry attitude control system by gas jet thrusters and recovery by two-stage parachute and airbags. Table 1 shows the specification of WIRES#015.
**Figure 4:** WIRES#015

### Table 1: WIRES#015 specifications

| Length       | [m]  | 4.6 |
|--------------|------|-----|
| Launch mass  | [kg] | 1000|
| Wing area    | [m²] | 2.68|

**DynDGA condition**

Table 2 shows the DynDGA condition. Terminating generation depends on simulation types.

### Table 2: DynDGA condition

| Number of individuals | 200 |
|------------------------|-----|
| Number of gene         | 24  |
| Number of characteristics | 40  |
| Clustering border      | $4 \times 10^4$ |
| Differential equation solution | $4^{th}$Runge-Kutta |
| Crossover method       | 0.5-Blend crossover |
| Selection method       | Elitist recombination |
| Mutation               | 0.1 |
| Migration step         | 10  |
| Differential equation step | 0.5 |

**Fitness**

The objective functions are defined as written in eqs. (1)-(6).

$$F = \frac{1000}{x_e + x_{err} + \psi_{err} + x_{obs}} \quad (1)$$

$$x_e = \frac{x_{flight}}{x_{base}} \quad (2)$$

$$x_{err} = 10 \frac{|\xi_t - \xi_i| + |\eta_t - \eta_i| + |h_t - h_i|}{x_{base}} \quad (3)$$

$$\psi_{err} = \frac{50|\psi_t - \psi_i|}{\pi} \quad (4)$$

$$x_{obs} = 0 \quad (5)$$

$$x_{base} = |\xi_t - \xi_i| + |\eta_t - \eta_i| + |h_t - h_i| \quad (6)$$

where $x_{flight}$ is trajectory length. In short, the objective function is the minimization of the summation of flight time, the difference between the target point and final point in terms of down-range, cross-range, altitude, azimuth, and the flight duration when the obstacle area is violated. However, the obstacle parameter is set to zero because the simulation doesn’t have obstacle area.

For calculating the fitness, the guidance system solves the differential equation of motion as in eqs. (7)-(19).
\[
m \frac{dV}{dt} = \frac{1}{2} \rho V^2 S_n C_D - mg \sin \gamma \quad (7)
\]
\[
m \frac{dy}{dt} = \frac{1}{2} \rho V^2 S_n \cos \phi - mg \cos \gamma \quad (8)
\]
\[
m \cos \gamma \frac{dy}{dt} = \frac{1}{2} \rho V^2 S_n \sin \phi \quad (9)
\]
\[
\frac{dh}{dt} = V \sin \gamma \quad (10)
\]
\[
\frac{d\xi}{dt} = V \cos \gamma \cos \psi \quad (11)
\]
\[
\frac{d\eta}{dt} = V \cos \gamma \cos \psi \quad (12)
\]
\[
C_L = 3.3232\alpha - 0.0574 \quad (13)
\]
\[
C_D = 3.146\alpha^2 - 0.1715\alpha + 0.0805 \quad (14)
\]
\[
d_a(t) = e a_{a_a} + (1 - e |a_{a_a}|) \sum_{n=1}^{3} \left( a_{a_n} \cos(n\omega t) + b_{a_n} \sin(n\omega t) \right) \quad (15)
\]
\[
\alpha(t) = d_a(t) \times \text{limit}_a \quad (16)
\]
\[
d_a(t) = e a_{a_a} + (1 - e |a_{a_a}|) \sum_{n=1}^{3} \left( a_{a_n} \cos(n\omega t) + b_{a_n} \sin(n\omega t) \right) \quad (17)
\]
\[
\phi(t) = d_a(t) \times \text{limit}_\phi \quad (18)
\]
\[
\begin{align*}
10 & \leq \alpha \leq 20 \\
-60 & \leq \phi \leq 60
\end{align*} \quad (19)
\]

where \(a_0, a_a, b_n, \text{ and } \omega\) are optimized variables, \(e\) is the user defined parameter and \(t\) is time.

**Other simulation condition**

Figure 5 shows a flight area image. Table 3 shows the initial conditions of the first trajectory. Table 4 shows the target conditions.

![Flight area image](image-url)

**Figure 5:** Flight area

| Table 3: Initial condition |
|-----------------------------|
| **Velocity**                | [m/s]  | 100 |
| Flight path angle           | [°]    | 0   |
| Azimuth                     | [°]    | 0   |
| Down range                  | [m]    | 3000|
| Cross range                 | [m]    | 0   |
| Altitude                    | [m]    | 5000|

| Table 4: Target condition   |
|-----------------------------|
| **Down range**              | [m]    | 0   |
| Cross range                 | [m]    | 0   |
| Altitude                    | [m]    | 1000|
| Azimuth                     | [°]    | 180 |
Figure 6 shows the outline of simulation flow. In this paper, there are 4 simulation patterns. First simulation pattern is single shot guidance. In this pattern, the guidance system generates an optimal trajectory for every 5 seconds. However, there are no inheriting data to use in the next optimization. Second pattern is continuous optimization. In this pattern, the guidance system continuously generates an optimal trajectory during the simulation, and it updates the optimal solution for every 100 generations. Third pattern is same as second pattern. In this pattern the guidance system updates the optimal solution for every 800 generations. Final pattern is also similar to second pattern. In this pattern the guidance system updates the optimal solution for every 10 generations.

Simulation Result:
Each simulation patterns were able to reach near the target position. Table 5 shows the outline of the simulation results. As the interval between the output solutions decreased, the total simulation time also decreased in the continuous simulation. However, the error of azimuth increases. From the fitness profile, continuous simulation has better fitness than single shot simulation.

In the real time implementation, the guidance system needs to set the interval not for the offspring generation but for calculation time. This is because the calculation time depends on the initial conditions. As a result, the interval time is based on the calculation time which is calculating the 100 generations.

Table 5: Outline of simulation result

|                  | Calculation time [s] | Error of distance [m] | Error of azimuth [°] |
|------------------|-----------------------|-----------------------|----------------------|
| Single shot      | 5167                  | 0.18                  | 6.42                 |
| Interval of 100 generation | 1082                  | 0.23                  | 39.6                 |
| Interval of 800 generation | 7897                  | 0.01                  | 16.9                 |
| Interval of 10 generation | 243                   | 104                   | 76.3                 |

Single shot generation
The simulation result is shown in Figure 7. This shows all the optimal trajectories produced. The symbol “*” is the initial position at which the trajectory is generated. Each trajectory could reach near the target point. Figure 8 shows the fitness value profile. Each fitness starts with a low value.
Interval of 800 generation
The simulation result is shown in Figure 9. This shows all the optimal trajectories produced. The symbol ‘*’ is the initial position at which the trajectory is generated. Each trajectory could reach near the target point, however the final trajectory’s azimuth has larger error. Figure 10 shows the fitness value profile. Each fitness value starts with a higher fitness value than single shot pattern, however each fitness value terminates with a lower fitness value than single shot pattern.

Interval of 100 generations
The simulation result is shown in Figure 11. This shows all the optimal trajectories produced. The symbol ‘*’ is the initial position at which the trajectory is generated. Each trajectory could reach near the target point. However, the final trajectory’s azimuth has larger error. Figure 12 shows the fitness value profile. Each fitness value starts with a higher fitness value than single shot pattern. The final fitness value is less than the single shot pattern.
Interval of 10 generations

The simulation result is shown in Figure 13. This shows all the optimal trajectories produced. The symbol “*” is the initial position at which the trajectory is generated. Earlier trajectory could not reach near the target point. However, final trajectory could reach near the target. Figure 14 shows the fitness value profile. Each fitness value starts with a higher value than single shot pattern. The final fitness value is less than the single shot pattern.

Conclusion:

This paper describes the simulation results of DynDGA onboard guidance system for experimental winged rocket in dynamic environment. From the results, the continuous generation type which has the interval set at 100 generation appears to be optimal than the other generation types. In future, authors continue the simulation for real time implementation and validate on the experimental winged rocket.
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