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An Overview of Evolutionary Algorithms toward Spacecraft Attitude Control

Matthew A. Cooper and Brendon Smeresky

Abstract

Evolutionary algorithms can be used to solve interesting problems for aeronautical and astronautical applications, and it is a must to review the fundamentals of the most common evolutionary algorithms being used for those applications. Genetic algorithms, particle swarm optimization, firefly algorithm, ant colony optimization, artificial bee colony optimization, and the cuckoo search algorithm are presented and discussed with an emphasis on astronautical applications. In summary, the genetic algorithm and its variants can be used for a large parameter space but is more efficient in global optimization using a smaller chromosome size such that the number of parameters being optimized simultaneously is less than 1000. It is found that PID controller parameters, nonlinear parameter identification, and trajectory optimization are applications ripe for the genetic algorithm. Ant colony optimization and artificial bee colony optimization are optimization routines more suited for combinatorics, such as with trajectory optimization, path planning, scheduling, and spacecraft load bearing. Particle swarm optimization, firefly algorithm, and cuckoo search algorithms are best suited for large parameter spaces due to the decrease in computation need and function calls when compared to the genetic algorithm family of optimizers. Key areas of investigation for these social evolution algorithms are in spacecraft trajectory planning and in parameter identification.

Keywords: trajectory optimization, spacecraft control, artificial intelligence, genetic algorithm, particle swarm optimization, ant colony, artificial bee colony, cuckoo, firefly, swarm intelligence, evolutionary optimization

1. Introduction

Evolutionary algorithm use has been steadily increasing in the number of published papers corresponding to an increasing number of applications over the past 20 years [1–8]. Originating as an alternative to traditional mathematical optimization techniques, the techniques now span across almost every discipline to include data compression, traveling salesmen, image processing, and more importantly for spacecraft: control theory [9–13], system identification [14–19], and trajectory optimization [20–25]. Randomly searching a solution space to perform a global optimization routine can be computationally expensive and time consuming. Traditional methods such as stochastic parallel gradient decent, newton's method,

and quadratic programming [26] are mathematical methods which rely mainly on the “steepness” of the gradients, or of the corresponding derivatives to follow the solution set to a zero-crossing gradient value and a potential optimum value. These methods are not easily implemented in discontinuous, or highly non-linear systems with a time-dependence such as in trajectory generation, and system identification of complex systems. One can perform a systematic, or random, search across an entire solution space, but the complex nature of some applications can limit the optimization to solution sets of only those within a small parameter space. Performing an exhausting search across an entire solution space can be considered the “brute force” method where the routine tries every single possible solution until the optimization criteria are met. For systems with a large parameter space with many variables, the computational cost might be too burdensome to arrive at a solution in a timely manner, and is certainly not relevant for a real-time application outside of a few cherry-picked examples. However, if a problem can be defined in an approachable way, evolutionary algorithms can provide a simpler and quicker way to find a viable solution. Due to the nature of these derivative free metaheuristic random search algorithms, the global optima may not be found but a suitable local optima that meets the optimization criteria can.

The most prominent evolutionary algorithm is the genetic algorithm officially introduced by John Holland in his 1975 book titled “Adaptation in Natural and Artificial Systems” [27] and its primary variants involving the concepts of chromosomes, elitism, parallel populations [28–30], and adaptation [31–33] which are derived from the concept of Darwinian evolution of animal species across many generations, also known as natural selection. Genetic Algorithms will be discussed more thoroughly in Section 2. The sister approach to natural selection based evolutionary algorithms are social-evolutionary algorithms also known as swarm intelligence which will be discussed in Section 3. Swarm intelligence is also a derivative free metaheuristic random search algorithm but with a slight modification on both selection criteria and on the definitions that spawn the “evolution”. Swarm intelligence optimization algorithms for astronomical applications can be sub-categorized into particle optimization and combinatorics. Particle optimization includes particle swarm optimization [34], firefly algorithm [35], and cuckoo search algorithms [36] which focus on a large parameter space with a correspondingly large solution space that may be impossible to evaluate with traditionally exhaustive optimization routines. The artificial bee colony optimization [37], and ant colony optimization [38] algorithms are designed for a smaller investigation swarm but can successfully navigate a problem defined as an infinite set of combinations such as the commonly referred to problem of a traveling salesman visiting a large number of cities.

2. Genetic algorithm

Genetic algorithms have been a staple of heuristic artificial intelligence approaches since its inception in the 1960s and later more formally introduced by John Holland in 1975 [27]. In the 1990s this kind of random search global optimization routine became more mainstream through the use of greatly increased processing speeds brought on by the personal computers any more importantly GPUs. Just like other evolutionary algorithms, genetic algorithms rely on a very specific parameter space defining the population characteristics, parent selection, and success criteria.

Biesbroek presents a parametric study on the fundamental parameters within a genetic algorithm application in [39] via three cases toward spacecraft trajectory optimization. The fundamental parameters include population size, mutation

probability, and cross-over probability. **Figure 1** illustrates the baseline genetic algorithm structure.

The first major step is in seeding a population. Seeding a population is done by presenting the algorithm an initial starting point to grow a population from. An alternative here is to randomly generate a population. A Gaussian distribution is one common approach. The parent population size is generally dependent on how many parameters are to be optimized via GA.

Holland described the genetic algorithm as being comprised of building blocks [27], which was later rederived by Goldberg [40] who related the population size with the quality of decisions and predicted that for an initial population of n , n^3 building blocks are potentially available in the algorithm. A rule of thumb is for m number of parameters the expected population required for convergence scales with the square root of the problem. More specifically, Harik showed that using probabilities, a more optimal population size can be described by Eq. (1) [41].

$$n = -2^{k-1} \ln(\alpha) \frac{\sigma_{bb} \sqrt{\pi m}}{d} \tag{1}$$

where k is the order of building blocks, α is the probability of GA failure, σ_{bb} is the average noise expected on the quality of building blocks, m is the number of the building blocks within the parameter minus one, and d is the difference between the best and the second best fitness values. In this definition, the noise is a description of how the building blocks create a member via the genetic evolution of the algorithm and how the resulting combinations may interfere in finding the optimal solution. In other words, the parent population can create noise hindering the convergence efficiency. With the expectation on the population size that it scales with $\sqrt{m}$, it can be seen how quickly the required population and therefore computational need increases with the number of parameters. A more recently derived rule of thumb is that for “small” parameter sets, the population size is effective if scaled with the number of parameters with 10 m , and for larger spaces the population size scales with $\ln(m)$ [42], where the definition of large is different for each author. For a simple parameter set GA can be quite effective for optimization

Figure 1.
Generic genetic algorithm flow diagram.

Figure 10.
Firefly search algorithm iteration illustration.

[61–63] in what can be considered as an introductory investigation by looking for initial successes in applying the FA toward these astronautical research areas.

3.3 Ant colony optimization search algorithm

The ant colony optimization (ACO) algorithm is another approach based off of the swarm behavior of insects, and was originally designed for combinatorial problems like the traveling salesman problem (TSP) where one tries to find the minimum path for an individual to traverse across n number of cities. In the instance of the traveling salesman, the salesman has a seemingly infinite number of combinations (but not really) to try but only wants to travel the shortest path, and to not repeat any stops along the way. The basic ant system, an earlier version of ACO, was presented by Dorigo in 1992 in his PhD thesis [38]. He presented a complex optimization algorithm based on the simultaneously simple and complex nature of foraging ants that would gain a large interest in the 1990s and later. Many variants and hybrids were presented by Dorigo and others. Most notably, offline pheromone updates, and pheromone evaporation was introduced which led to the more common ACO in 1999 [64, 65]. The concept of pheromones will be discussed shortly.

Figure 11 illustrates at a high-level the flow of the ant colony optimization routine. The algorithm is initiated with a given set of parameters and objective function. Next, an initial set of solutions is populated. This is the first round of traveling ants looking for an optimal solution. The given problem is defined and broken apart such that the optimization routine will look for the optimal set of these building blocks in order to minimize the objective functions, or distance in the realm of the traveling salesman. At this point the pheromone level will be calculated. The pheromone is laid out such that each ant lays the same amount of pheromone out on the path that it traverses. This pheromone makes the links between different combinatorial building blocks attractive. If more than one ant traverses a similar segment the pheromone level will increase on that path segment, with an end result of the most common path being the most attractive.

With the most traversed paths being the most attractive, one may notice that there could be a strong potential for the algorithm to get “stuck” in a local minima. The ACO algorithm includes what is know as a local pheromone update, which means that either only the last segment of a successful path will include the pheromone, or that the end segment will be delivered a heavier weight of pheromone by the one ant who achieved the best path in the current iteration. Alternatively, the best path so far (out of all the iterations) may receive that additional pheromone instead. At this point the solution space is evaluated to see if a viable global solution

Figure 11.
Ant colony optimization search algorithm flow chart.

was found. If not, then the current ants will go through an exponential pheromone decrease before starting the next iteration in the optimization process. This pheromone decay reduces the impact of hysteresis on the solution space and helps prevent premature convergence.

On the following iteration the current ant population will then create a new set of paths to achieve a solution in the population. Each link will follow pseudorandom proportional rule, which uses a uniform distribution probability weighted by the segment pheromone values to decide on each link in the path. Once all ants create the new population of solutions another iteration of pheromone decisions will follow. This entire process will continue until convergence criteria are met.

Ant colony optimization has been successfully used for problem sets that can be discretized into a combinatorial problem such as in path planning [66–68], trajectory optimization [21, 69], and even in spacecraft load bearing [70].

3.4 Artificial bee colony algorithm

Artificial bee colony (ABC) optimization is a derivative of both the bees system presented in 1997 by Sato and Hagiwara and the bee colony optimization by Teodorovic and Dell in 2005 [4], and was introduced later in 2005 by Karaboga [37]. The underlying algorithm flow chart is illustrated in **Figure 12** and involves three types of bees: onlookers, employed bees, and scouts. At the start of the algorithm, the routine parameters are initialized, and an initial population of food sources is generated via a uniform random distribution across the solution space. The population of food sources is discovered by employed bees and the quality of the food source is evaluated via an application specific fitness function. The employed bees then randomly search for a new food source, and if that food source is of better quality, then it becomes the primary food source. If not, then the new food source is abandoned. This is called a greedy search. Meanwhile, the onlooker bees observe the actions of the employed bees, and observe their communication dance through the lens of a randomly distributed variable. This represents the decision tree on which employed bee an onlooker will follow, or if it will create a new search. If the onlooker searches for a new food source, it will choose based on a random recombination of two solutions nearby. When a food source is not picked up by the onlookers when they transition to the employed bees, that food source is

Figure 12.
Artificial bee colony algorithm flow chart.

now considered to be abandoned and will not be a part of the known current solution space. The next step is to repeat the search for new sources, a greedy selection, and the corresponding employed bee dance to randomly attract an onlooker to the known food source.

Similar to the ant colony optimization algorithm, the artificial bee colony algorithm is primarily designed for a combinatorics based problem where the potential solution can be discretized into an array of building blocks that can be rearranged and mutated to find an optimum solution. Additionally, the ABC algorithm has been used for trajectory optimization [71], parameter optimization [72, 73], and remote sensing applications [74, 75].

3.5 Cuckoo-search algorithm

Another metaheuristic search algorithm is introduced with the cuckoo search algorithm (CSA). This approach mimics the parasitic brood behavior in certain species of the cuckoo bird. This type of bird has a fascinatingly aggressive reproduction strategy which is the heart of the CSA. Quite a few species of cuckoos participate in the obligate brood parasitism which means that they will lay their eggs in the nests of other birds [36]. The key to the success of the individual cuckoo is dependent on the cuckoo's ability to produce an egg that is able to mimic, or approximate, the host nest eggs such that the host nest mother bird can not distinguish the cuckoo egg from her own. The cuckoo egg will hatch before the host eggs, and ensure dominance in the nest and thus prolong their survival.

Taking this concept to an optimization algorithm it can be illustrated as seen in **Figure 13**. Step one is to initialize the algorithm and generate a population of host nests. Each host nest has a single potential solution to be compared against. The next step is to evaluate the initial population of nests with the defined fitness function. Once the fitness function is evaluated for each cuckoo egg, the next step is for the cuckoo to take flight via a classical Levy flight path [36]. This is a type of step pattern is a heavy-tailed random walk similar to that of a fruit fly, which are observed to jolt out in a straight direction then randomly turn a sharp turn at a random angle. The desired behavior is described in Eq. (10).

$$x_{t+1} = x_t + sE_t \tag{10}$$

Figure 13. Cuckoo-search algorithm flow chart.

Figure 14. Cuckoo-search algorithm iteration illustration.

where x_{t+1} is the position in the next iteration, s is the step size, and E_t is a zero-mean random Gaussian draw to mimic Levy flights. Once each cuckoo take a flight to a “new” nest, the fitness function is then calculated again to evaluate the new population of potential solutions. If the solution criteria are not met, then this process of flying from nest to nest will continue until convergence as illustrated in **Figure 14**. Each individual will take a random walk biases by the direction of the current best solution within the group.

Yang’s and Deb’s seminal work on the CSA illustrated an enormous computational cost savings when compared to the genetic algorithm and the particle swarm optimization Algorithm as each algorithm was used to find the solution to a handful of standard challenging mathematical functions: Michalewicz, Rosenbrocks, Schwefels, Rastrigins, with a 96, 89, 96, and 91% decrease in the number of required fitness function evaluations when compared to a GA solution respectively [36].

4. Conclusions

With a prevalence of evolutionary algorithms focused on solving trajectory generation, path planning, remote sensing, control theory, and parameter

identification for aeronautical and astronautical applications it is a must to review the fundamentals of the most common evolutionary algorithms being used for those applications. Genetic algorithm, particle swarm optimization, firefly algorithm, ant colony optimization, artificial bee colony optimization, and the cuckoo search algorithm are presented and discussed with an emphasis on astronautical applications. In summary, the genetic algorithm and its variants can be used for a large parameter space but is more efficient in investigating a smaller parameter space, less than 1000 parameters in the chromosome. It is found that PID controller parameters, nonlinear parameter identification, and trajectory optimization are applications ripe for the genetic algorithm. Ant colony optimization, and artificial bee colony optimization are optimization routines more suited for combinatorics, such as with trajectory optimization, path planning, scheduling, and spacecraft load bearing. Particle swarm optimization, firefly algorithm, and cuckoo search algorithms are best suited for large parameter spaces due to the decrease in computation need and function calls when compared to the genetic algorithm family of optimizers. Key areas of investigation for these social evolution algorithms are in spacecraft trajectory planning, and in parameter identification.

Evolutionary algorithms have been shown to have a great potential to solve challenging problems that traditional optimization routines may not be able to tackle due to large computational need to support an exhaustive search of the solution space. The reader should now have the tools to take the foundational material presented here, to review the referenced sources, and conduct their own deep dive in an application area of interest.

Disclaimer

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Author details

Matthew A. Cooper^{1*} and Brendon Smeresky²

1 Air Force Research Laboratory, Albuquerque, New Mexico, USA

2 Naval Postgraduate School, Monterey, California, USA

*Address all correspondence to: matthew.cooper.17@us.af.mil

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