AIRFOIL SHAPE PARAMETERIZATION FOR EVOLUTIONARY COMPUTATION

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Abstract

This lecture addresses two kinds of representation issues required for successful application of evolutionary computation to aerodynamic design. The first issue is how to represent a large number of continuous design variables in evolutionary computation. The concept of dynamic coding is applied to the floating-point representation to search a large continuous domain effiecintly. The second issue is how to choose design variables proper for airfoil definition. Several airfoil definition techniques are compared through sample optimization cases.

1 Introduction

Application of Genetic Algorithms (GAs) to aerodynamic design is of strong interest because GAs are robust and capable of finding global optima. However, such application may not be trivial. Aerodynamic design has to search an optimal shape in a large continuous domain. Since the aerodynamic performance is sensitive to its shape, the aerodynamic shape has to be described precisely. It requires a large number of design variables, and thus requires a continuous domain of high dimensions. Such a large continuous domain is indispensable to the aerodynamic design.

Finding a global optimum in a large continuous domain is challenging even for GAs. Traditional GAs use the binary representation that evenly discretizes a real-numbered design space. Although such binary-coded GAs have been successfully applied to a wide range of design optimization problems, they suffer from disadvantages, when applied to real-world problems involving a large number of continuous design variables. Since binary substrings representing each parameter with a desired precision are concatenated to represent an individual, the resulting string encoding a large number of design variables would wind up a huge string length. For example, for 100 variables with a precision of six digits, the string length is about 2000. GAs would perform poorly for such design problems. Previous applications have been kept away from this problem by sacrificing precision or narrowing down search regions prior to the optimization. However, such approaches might exclude the region that actually contains the global optimum.

Another drawback of the binary-coded GAs applied to parameter optimization problems in continuous domains comes from discrepancy between the binary representation space and the actual problem space. For example, two points close to each other in the actual problem space might be far away in the binary representation space. It is still an open question to construct an efficient crossover operator that suits to such a modified space.

A simple solution to these problems is the use of the floating-point representation of real-numbered parameters. In these real-coded GAs, an individual is coded as a vector of real numbers corresponding to the design variables. The real-coded GAs are easier to be contstructed because the floating-point representation is conceptually equivalent to the real design space, and moreover, the string length reduces to the number of design variables. However, even the real-coded GAs often lead to premature convergence when applied to aerodynamic shape designs with a large number of design variables.

Therefore, the representation of an aerodynamic design candidate is an important issue for the application of GAs. The first part of this lecture addresses the representation of a large continuous domain in GAs using the concept of dynamic coding [1-4]. The dynamic coding is able to search a large domain efficiently by adapting the search region or population to a region of higher fitness during the evolution.

The second half of the lecture addresses how to represent an aerodynamic shape, in particular, an airfoil shape. There are many ways to define airfoil shapes. Even if they are mathematically equivalent, they may behave differently in evolutionary computation. Typical airfoil definitions will be examined empirically here using sample optimization problems.

2 Adaptive Range Genetic Algorithms

In the binary GAs, a more sophisticated approach to discretize a continuous domain is to dynamically alter the coarseness of the search space referred to as dynamic coding. In [1], Krishnakumar et al. presented Stochastic Genetic Algorithms (Stochastic GAs) to efficiently solve problems with a large number of real design parameters. The key features of Stochastic GAs are:

1. Each binary number represents a region of the real space instead of a single point to maintaining good precision with the small string length.
2. Those regions adapt during the optimization process according to the 1/5th success rule as Evolutionary Strategies (ESs) to improve efficiency and robustness.

The Stochastic GAs have been successfully applied to Integrated Flight Propulsion Controller designs [1] and air combat tactics optimization [2]. As they explained, the Stochastic GAs bridge the gap between ESs and GAs to handle large design problems.

Adaptive Range Genetic Algorithms (ARGAs) are another approach using dynamic coding proposed by Arakawa and Hagiwara [3] for binary-coded GAs. The essence of their idea is to adapt the population toward promising design regions during the optimization process, which enables efficient and robust search in good precision while keeping the string length small. Moreover, ARGAs eliminate prior definition of boundaries of the search regions since ARGAs distribute design candidates according to the normal distributions of the design