Genetic algorithms, game theory and hierarchical models : application to CFD and CEM problems

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Abstract

This paper is the companion paper of *Genetic algorithms, game theory and hierarchical models : some theoretical background*. It presents several applications of the ideas and algorithms discussed in that paper. These applications belong either to the field of Computational Fluid Dynamics or to the field of Computational Electromagnetics.

Part I

Computational Fluid Dynamics

The applications considered in this part are focused on continuous optimization problems. The problems we deal with are non-convex and tend to have a series of local optima beside the global optimum.

We have applied genetic algorithms to the field of airfoil optimum design because the deterministic methods that are widely used in aerodynamics are not really robust towards local optima, even if they converge faster than GAs [17].

1 Reconstruction Problem : RAE2822 airfoil

1.1 Problem definition

The first problem we present is a reconstruction problem: it is an inverse problem that consists in finding the shape (denoted γ) of an airfoil which realizes a surfacic target pressure distribution for a given Euler flow condition [9]. This problem has the following formulation:

Minimize $J(\gamma)\ with\ J(\gamma) = \frac{1}{2}\int_{\gamma} |p_{\gamma} - p_{target}|^2 d\gamma$

Where p_{target} is a given target pressure and p_γ is the actual flow pressure on γ.

We first compute the pressure distribution for a given shape thanks to a CFD solver [5]. Then, we start the optimization process with another shape (either a shape corresponding to a given starting point or a randomly generated shape) and try to retrieve the first shape. Let n be the number of discretization points of the profile. The following discretized cost function f_n (fitness) is used by both the gradient and genetic approaches:

$$f_n(\gamma) = \frac{1}{2}\sum_{i=1}^{n}(P_i^\gamma - P_i^{target})^2$$

Where P_γ is the pressure of the evaluated shape via an Euler flow analysis solver and P^{target} denotes the pressure distribution of the target shape.

1.2 representation

The most natural way of representing an airfoil shape is point by point. However, if those points are taken as parameters, there must be at least a hundred of them to get a fine local tuning (which means a very high-dimension search space). This why we chose a Bezier Spline representation. We use a seven-order Bezier Spline, which corresponds to two fixed points (one at each extremity) and six control points. A Bezier spline of order n is defined by the Bernstein polynomes $B_{n,i}$:

$$Q(t) = \sum_{i=0}^{n} B_{n,i}P_i \text{ with } B_{n,i} = C_n^i t^i (1-t)^{n-i}$$

Where t denotes the parameter of the spline taking values in [0,1], P_i are the coordinates of the control points and $C_n^i = \frac{n!}{i!.(n-i)!}$.

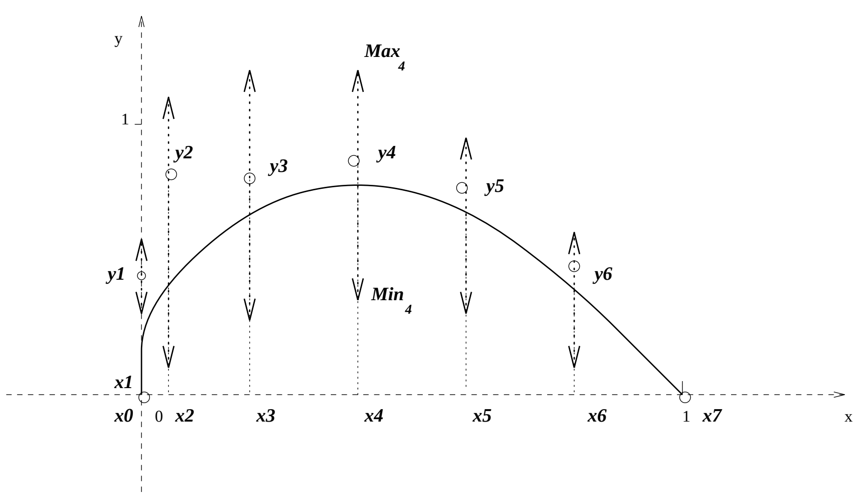

Figure 1: Bezier Spline for leeward side