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Quijada Pioquinto J.G.

GENERATION OF A DATABASE OF AIRFOILS WITH BEZIER-PARSEC PARAMETERS

Bezier-PARSEC parameters are used to describe profile geometry in aerodynamic shape optimization processes due to the reduced number of design variables and their ability to simulate airfoils of multiple families. This favorable feature is ideal for standardizing a set of profiles to be used in deep neural network training. The main challenge of creating a data set for training a neural network is to obtain a lot of data with the same parameters to describe it. This paper offers a proposal to generate a database of profiles with Bezier-PARSEC parameters, using the algorithm of Adaptive Differential Evolution based on the History of Success and methods of population size reduction.

Keywords: SHADE algorithm, parameterization Bezier-PARSEC, population size reduction methods.

Introduction. In 2004, Rogalsky in his doctoral thesis proposed the new Bezier-PARSEC (BP) parameterization method for airfoils [1], [2]. This new method aims to accelerate the convergence of evolutionary aerodynamic optimization processes. Rogalsky and Derksen proved the abilities to represent differents airfoils with BP parameters (symmetrical and asymmetrical airfoils, high and low lift airfoils, wing airfoils and turbomachinery use airfoils). These tests were performed with the differential evolution (DE) algorithm, and the objective function was the geometric deviation [3], [4]. The results were satisfactory, showing that one could have a small number of design variables (which implies a smaller number of individuals per generation), which accelerates the optimization process without the need to risk the globality of the search for the optimal value [1], [2], [3]. This characteristic of BP parameters is what allows to represent airfoils of different families (NACA, EPPLER, GOE, etc.). Although the DE algorithm provides a good speed to find the BP parameters of a profile, in this work a faster option is provided.

To acelerate up the optimization process, it is proposed to use an evolutionary algorithm that implements methods of population reduction (PSR): the Success-History based Adaptive DE (SHADE) algorithm. Success-History based adaptation is a mechanism for parameter adaptation based on a historical memory of successful parameter settings that were previously used found during the run [5]. The SHADE algorithm is used for the adaptability of incorporating PSR methods [6], [7], [8], [9].

1. Bezier-parsec parameterization. Rogalsky and Derksen developed two variants of BP parameters based on the degree of the polynomial of the Bezier curves used, the parameters BP3333 (with 4 third-degree curves and 12 variables) and the parameters BP3434 (with 2 third-degree curves and 2 fourth-degree curves and 15 variables) [1], [3]. In this work only the BP3333 variant was evaluated. The airfoils created with the BP3333 parameters are represented by four third-degree Bezier curves, two to define the thickness curve (leading and trailing curves) and two to define the camber curve (leading and trailing curves). In fig. 1 shows the graphical representation of each parameter.

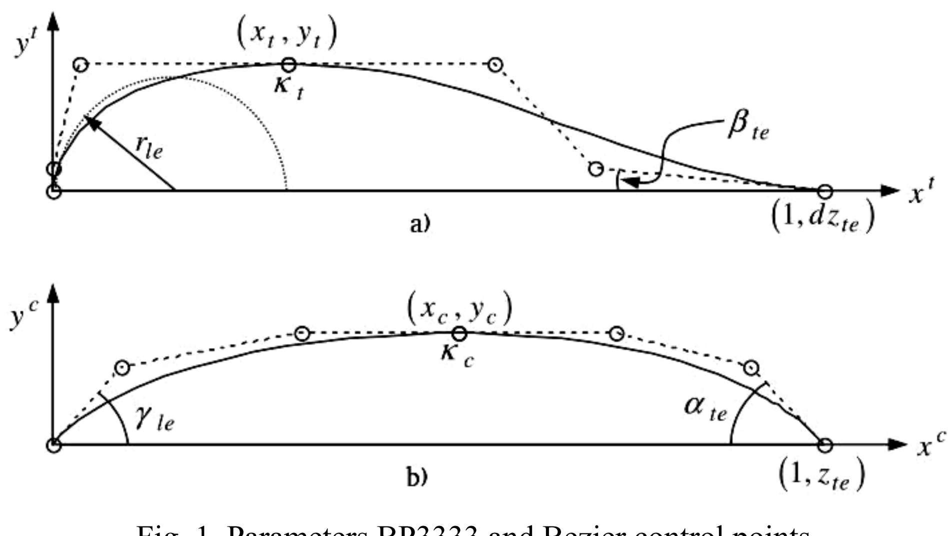

Fig. 1. Parameters BP3333 and Bezier control points,
a) thickness curve, b) camber curve [3].

2. Evolutionary algorithms. The variant of the DE algorithm used by Rogalsky and Derksen is /rand-to-best/1. They considered a value of the crossing scale factor *CR* equal to 1, the crossing operator was omitted. The mutation operator is defined by [2].

$$u_{i,g} = x_{i,g} + F\left(x_{B,g} - x_{i,g}\right) + F\left(x_{b,g} - x_{c,g}\right)$$

The SHADE algorithm uses an archive set (A) to store the worst vectors of each generation. The maximum size of the $|A|$ archive set is defined by the user. When the set is saturated, the amount of leftover elements is randomly removed. A allows to give diversity of individuals to the following generations of vectors.

The mutation operator is current-to-pbest/1:

$$u_{i,g} = x_{i,g} + F_i\left(x_{pB,g} - x_{i,g}\right) + F_i\left(x_{r1,g} - x_{r2,g}\right)$$

where $x_{pB,g}$ is a randomly chosen vector from the elite group of size $N \times p$ ($p \in [0,1]$); $x_{r1,g}$ is a chosen vector from the current population P_g; $x_{r2,g}$ is a chosen vector from the set $P \cup A$ ($x_{pB,g} \neq x_{i,g} \neq x_{r1,g} \neq x_{r2,g}$).

The mutation scale factor F_i is randomly chosen from a historical memory with elements $M_{F,k}$ ($k = 1, \ldots, H$). The random choice is made by a Cauchy distribution, where an element $M_{F,ri}$ from the historical memory is randomly chosen.

$$F_i = randc_i\left(M_{F,ri}, 0{,}1\right), \tag{1}$$

if the value obtained from Fi in (1) is greater than 1, the result is truncated to 1, and if the result is less or equal to 0, (1) is reapplied until a valid result is obtained. The values of the historical memory are updated in each generation [5].

After creating a new generation a population reduction method is applied: linear reduction (L-PSR) [6]

$$N_{g+1} = round\left[\left(\frac{N_{min} - N_0}{NFE_{max}}\right) NFE + N_0\right],$$

exponential reduction (E-PSR) [7]

$$N_{g+1} = round\left[N_0 \left(\frac{N_{min}}{N_0}\right)^{\frac{NFE}{NFE_{max}}}\right],$$

parabolic reduction (P-PSR) [8]

$$N_{g+1} = round\left[\frac{N_{min} - N_0}{(NFE_{max} - N_0)^2}(NFE_{max} - N_0)^2 + N_0\right],$$

or nonlinear reduction (NL-PSR) [9].

$$N_{g+1} = round\left[\frac{N_{min} - N_g}{(NFE_{max} - N_g)^2}(NFE_{max} - N_g)^2 + N_g\right],$$

where N_{min} – minimum population, N_0 – initial population, NFE_{max} – maximum number of functions evaluated, NFE – the current number of functions evaluated.

3. Airfoils representation tests

To test the effectiveness of the SHADE algorithm with the PSR variants, representation tests were performed on 34 general aviation airfoils, and the number of target functions evaluated to achieve the optimal value established with the algorithm used by Rogalsky and Derksen were compared. In all cases, equation

$$\|y - y^T\|_{L_2} = \sqrt{\sum (y_i - y_i^T)^2}$$

(9) was used as an objective function. The stopping criterion was that the cost limit was less than 0,01. The population size of first generation is N_0 = 150. The intervals for each BP parameter are shown in table 1. The limit on the number of functions evaluated for all cases was 20000. For the case of DE algorithm, a mutation scale factor value F = 0,85 was used [1], [2], [3]. For the use of SHADE algorithm the following input values were taken: $N_{min} = 4$, $|A| = 1{,}4$, $N_0 = 10D$, $H = 6$, $p = 0{,}11$.

Table 1. BP3333 parameter ranges for representing general aviation airfoils.

BP3333 parameter	Interval
r_{le}	[-0,05; -0,0005]
x_t	[0,25; 0,45]
y_t	[0,04; 0,12]
k_t	[-0,82; -0,2]
β_{te}	[0,01; 0,4]
γ_{le}	[0,005; 0,4]
x_c	[0,2; 0,85]
y_c	[0,01; 0,07]
k_c	[-1,5; -0,05]
α_{te}	[0,01; 0,6]
dz_{te}	[0,0; 0,002]
z_{te}	[0,0; 0,0]

Table 2 shows the average values of NFE to achieve the established convergence.

Each case was tested 51 times. The SHADE E-PSR algorithm proved to have the best convergence rate, being best in 26 out of 36 cases. Overall, the SHADE E-PSR algorithm required fewer evaluated functions than the original algorithm, achieving a difference of approximately 1200 evaluated functions.

Table 2. NFEs required for convergence to airfoils (+ better convergence speed).

Airfoil	DE/rand-to-best/1	SHADE L-PSR	SHADE E-PSR	SHADE P-PSR	SHADE NL-PSR
CLARK-Y	7801	6848	6602	8799	5705+
CLARK-YH-11	3358	2700	2409+	3392	3175
CLARK-YH-20	4009	2569	2441+	3306	2840
EPPLER 231	4360	3965	3474+	4406	4052
EPPLER 334	7058	5133	4542+	5542	5092
EPPLER 558	5200	4180	3606+	4179	3935
EPPLER 562	3460	3427	2950+	3246	3298
FX 61-163	6110	5155	4111+	5517	4703
FX 61-184	12960	6638	5560+	7441	5777
FX 66-S-171	12459	6325	5184+	7019	5500
FX 66-S-196	6860	4549	3847+	5292	4515
GOE 398	3658	4088	2946+	4434	3581
GOE 446	4760	4296	3502+	4916	4453
GOE 477	2705	2357+	2513	2509	2566
GOE 526	3263	2624	2413+	2773	2419
GOE 593	3563	2460	2042+	2599	2596
GOE 611	2753	3243	2361+	2923	2915
GOE 796	2959	1732+	2397	2331	2195
LOCKHEED C-5A	3460	3037	2840+	3597	3917
ME-163	1400+	1785	1522	1558	1790

Table 2 (cont.)

Airfoil	DE/rand-to-best/1	SHADE L-PSR	SHADE E-PSR	SHADE P-PSR	SHADE NL-PSR
NACA 2412	1660	1842	1571	1469+	1881
NACA 4412	2406	1951	1572+	1946	1786
NACA 4418	2659	1949	1837+	2035	1998
NACA 6412	4604	3725	3474+	4093	4008
NACA 63-212	2054	2573	2019+	2273	2765
NACA 63-412	3154	3119	2746+	2833	2811
NACA 64A410	3253	2962	2683+	3071	2939
NACA 24112	6505	4939	5154	5554	4825+
TSAGI 718	2907	2620	2374+	2717	2698
TSAGI 84614	2151	2138	1689	2006	1646+
TSAGI A-9	1503+	1536	1692	2095	2314
TSAGI A-18	2262	2034	2021	1976+	2314
TSAGI B-12	2707	2410+	2572	2834	2697
TSAGI B-16	5050	4263	3541+	4178	3822
TSAGI D-2-14	4150	4283	3916+	4323	4345
TSAGI P-II-18	2950	2467	2023+	2688	2368
Avg. NFEs	4226	3386	3004	3663	3340

Conclusion. The proposal to use the SHADE algorithm with the four variants of PSR obtained a better convergence speed compared to the algorithm proposed by Rogalsky and Derksen, the SHADE E-PSR variant being the best results obtained, in 72% of cases obtained the fastest convergence, giving a saving of 1200 functions approximately. This amount of saved functions is considerable when performing reverse aerodynamic design processes, such as obtaining BP parameters from 800 airfoils to create a database for training a neural network.

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