A New Evolutionary Algorithm for Ground to Flight Data Correlation

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Abstract

In hypersonic vehicle design, it is very difficult/expensive to simulate the environment in flight. Therefore, it is of key important to predict the aerodynamic coefficients of the flight vehicle using wind-tunnel and flight-test data. The task is called ground to flight data correlation, also shorten as ground/flight correlation. A number of methods have been applied to ground/flight correlation, including extrapolation [1], least squares regression [2], artificial neural network [3, 4] and maximum likelihood method [5]. However, all these methods are based on a certain model structure and optimize the parameters in the model. This is, in many cases, unreliable. To find an optimal model structure will definitely improve the predicted results.

In this study, we suggest searching the best model structure from a functional space $\mathcal{F}$ with collected data $\{\{x_{i1}, x_{i2}, \cdots, x_{in}; y_i\}\}_{i=1}^{N}$, which can be described as $f^* = \arg\min_{f\in\mathcal{F}} \sum_{i}^{N} \|f(x_{i1}, x_{i2}, \cdots, x_{in}) - y_i\|$.

Genetic programming [6] is a candidate for this optimization problem. However, its tree-based representation makes it difficult (although not impossible) to be implemented in general-purpose programming languages such as C/C++ and Fortran. To overcome this difficulty, M. O'Neill and C. Ryan proposed a grammatical evolution (GE) [7] in 2001. However, GE is still not so easy to use. First, the implementation of GE is complicated because it needs an additional function parser for the encoding and decoding process. Next, the incomplete mapping and extra codons problems [7, 8] are common but difficult to handle.

In this paper, a new evolutionary algorithm, parse-matrix evolution (PME), for flight data correlation is proposed. A chromosome in PME is a parse-matrix with integer entries. The mapping process from a chromosome to its model function is based on a mapping table. PME can easily be implemented in any programming language and free to control. Furthermore, it does not need any additional function parsing process. Numerical results show that PME can solve the symbolic regression problems effectively (see Table 1).

Table 1: Test models and performance of PME

no.	Dim	Target model	Domain	no.samples	ave no.eval	ave no.start
1	1	$x^2 - \sin x$	$[1,3]$	8	3230	4.8
2	1	$\sin x + 2x$	$[1,3]$	8	2071	1.1
3	1	$\cos x^2 - x$	$[1,3]$	8	2603	2.3
4	1	$\sin x + \cos x - x$	$[1,3]$	8	3646	7.4
5	2	$x_1 + 2x_2$	$[1,3]^2$	16	1047	1.0
6	2	$(x_1 + x_2)/x_2$	$[1,3]^2$	16	1701	1.3
7	2	$\sin(x_1 + x_2)$	$[1,3]^2$	16	1537	1.0
8	2	$\cos(x_1 + x_2) - x_2$	$[1,3]^2$	16	2798	1.5
9	2	$\ln(x_1 + x_2)$	$[1,3]^2$	16	1584	1.2
10	2	$x_1 - e^{x_1+x_2}$	$[1,3]^2$	16	3593	1.8
11	2	$\ln(x_1 + x_2) + \sin(x_1 + x_2)$	$[1,3]^2$	16	4911	5.7
12	2	$\sin(x_1^2 - x_2) + \ln(x_1 + x_2)$	$[1,3]^2$	16	7637	13.2
13	3	$x_1 + x_2 - x_3$	$[1,3]^3$	64	4505	1.9
14	3	$x_1x_2 - x_3$	$[1,3]^3$	64	3164	2.7
15	3	$\sin(x_1x_2) + x_3$	$[1,3]^3$	64	3302	11.6

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