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Target shape design optimization by evolving B-splines with cooperative coevolution☆

Zhenyu Yang[a,*], B. Sendhoff[b], Ke Tang[c], Xin Yao[c,d]

[a] Zhuiyi Technique Inc., Shenzhen 518000, China
[b] Honda Research Institute Europe GmbH, Germany
[c] USTC-Birmingham Joint Research Institute in Intelligent Computation and Its Applications (UBRI), School of Computer Science and Technology, University of Science and Technology of China, Hefei 230027, China
[d] Centre of Excellence for Research in Computational Intelligence and Applications (CERCIA), School of Computer Science, University of Birmingham, Edgbaston, Birmingham B15 2TT, UK

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ABSTRACT

With high reputation in handling non-linear and multi-model problems with little prior knowledge, evolutionary algorithms (EAs) have successfully been applied to design optimization problems as robust optimizers. Since real-world design optimization is often computationally expensive, target shape design optimization problems (TSDOPs) have been frequently used as efficient miniature model to check algorithmic performance for general shape design. There are at least three important issues in developing EAs for TSDOPs, i.e., design representation, fitness evaluation and evolution paradigm. Existing work has mainly focused on the first two issues, in which (1) an adaptive encoding scheme with B-spline has been proposed as a representation, and (2) a symmetric Hausdorff distance based metric has been used as a fitness function. But for the third issue, off-the-shelf EAs were used directly to evolve B-spline control points and/or knot vector. In this paper, we first demonstrate why it is unreasonable to evolve the control points and knot vector simultaneously. And then a new coevolutionary paradigm is proposed to evolve the control points and knot vector of B-spline separately in a cooperative manner. In the new paradigm, an initial population is generated for both the control points, and the knot vector. The two populations are evolved mostly separately in a round-robin fashion, with only cooperation at the fitness evaluation phase. The new paradigm has at least two significant advantages over conventional EAs. Firstly, it provides a platform to evolve both the control points and knot vector reasonably. Secondly, it reduces the difficulty of TSDOPs by decomposing the objective vector into two smaller subcomponents (i.e., control points and knot vector). To evaluate the efficacy of the proposed coevolutionary paradigm, an algorithm named CMA-ES-CC was formulated. Experimental studies were conducted based on two target shapes. The comparison with six other EAs suggests that the proposed cooperative coevolution paradigm is very effective for TSDOPs.

1. Introduction

Design optimization has been an important area of research for many years [1]. In recent years, as robust optimizers with excellent ability in handling non-linear and multi-model objective functions, evolutionary algorithms (EAs) have successfully been applied to structural design optimization problems [2–4], especially in the field of aerodynamics, e.g. [5–7]. However, for real-world applications, especially in the area of aerodynamic design optimization, evaluation of a given design solution often requires high computational efforts such as the evaluation with Computational Fluid Dynamics (CFD) tools. The search for the most appropriate algorithm including the design representation and its parameterization based on computationally expensive CFD simulations would be very time consuming and for complex three-dimensional shapes currently impossible.[1] Therefore, miniature models or highly

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* Corresponding author.
E-mail addresses: zhyuyang@ieee.org (Z. Yang), bernhard.sendhoff@honda-ri.de (B. Sendhoff), ketang@ustc.edu.cn (K. Tang), x.yao@cs.bham.ac.uk (X. Yao).

[1] According to the experience in Honda Research Institute Europe GmbH, the calculation time for a detailed CFD analysis of a complex 3D structure takes roughly one day parallelized on several compute nodes.

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simplified CFD models have been suggested to ease the computational load in the early conceptual algorithmic phase. **Target Shape Design Optimization Problems** (TSDOPs) [8,9] have been put forward as miniature models in particular to test the usage of specific design representations. Although it is known that neither miniature models like TSDOP nor simplified CFD models correlate with the detailed CFD analysis, individual algorithmic issues can be studied and results successfully transferred to real-world optimization problems. Given a **target shape**, the TSDOP is defined as minimizing the distance between the target shape and the designed shape with respect to an appropriate distance measure. We focus on TSDOP in this paper, since the interplay between representation and algorithm is the main contribution of this work.

Evolutionary computation for TSDOPs was first investigated in [8], and then further studied in [10–12]. Generally speaking, they mainly focus on the following three issues which are very crucial in applying EAs to TSDOPs.

1 Representation: Representing the shape is the initial step and it determines the landscape of the search space. A number of characteristics, such as completeness, causality and compactness, have been suggested in [5] as the required properties of a suitable representation. A commonly used representation is the parameterized B-spline curves or surfaces [8,12]. Given a B-spline as the geometry representation, the objective parameters of TSDOP consist of the coordinates of the control points and the corresponding knot vector(s).

2 Fitness evaluation: For TSDOPs, since shapes are often represented by a set of sampled points, the designed shape can be evaluated by calculating the distance over two sets of points sampled, respectively from the target shape and the designed shape with respect to an appropriate distance metric, e.g. the commonly used averaged symmetric Hausdorff distance [8]. An improved fitness metric has also been proposed in [12] to alleviate the problem of wrongly assigning good quality shapes to bad.

3 Evolution: This step determines the driving force of evolution. With a B-spline as the geometry representation, existing efforts for this issue can be classified into two main categories: (i) Represent the designed shape with a predefined number of control points, and then optimizes the coordinates of control points and the knot vector with a certain EA; (ii) Represent the designed shape with **adaptive encoding** [8], which starts from a minimal representation length, and then optimize the coordinates of control points with a certain EA, and meanwhile increase the number of control points during evolution with a random **knot insertion** [13] algorithm. The first kind of evolution paradigm has at least two obvious drawbacks. Firstly, for an unknown target shape, it is often very difficult to determine the optimal number of control points. That is why the adaptive encoding scheme has been proposed. Secondly, it is unreasonable to optimize the control points and knot vector simultaneously using those EAs in which crossover is the necessary or essential operator. The reason is that knot vector and control points of B-spline are highly correlated. It makes no sense to perform crossover between two control-point sets whose corresponding knot vectors are different.[2] As for the other paradigm using adaptive encoding, although it has been proven better than the first one, the main difficulty is that the variation of the knot vector can only be obtained through irreversible knot insertion operations. Random knot insertion method is often adopted since it is very difficult to determine the optimal insertion position during evolution. This will at best limit flexibility of the designed shape and in the worst case take a risk to introduce very bad knot position.

[2] The reason will be demonstrated in Section 2.3.

For the issue of representation, we can still use a B-spline with adaptive encoding, since it has been verified as an effective choice [8–12]. For fitness evaluation, the only thing we can do is to provide a similarity metric, and eventually we have to abandon it because we need to use CFD tools for real-world applications. So among the three issues, we are mostly interested in the third one, i.e., designing appropriate evolution paradigm for TSDOPs.

In order to develop a more effective evolution paradigm for TSDOPs, we propose a new coevolutionary paradigm in this paper to evolve the control points and knot vector of a B-spline separately in a cooperative manner. This kind of evolution model is called Cooperative Coevolution (CC) [14,15], which was originally proposed to solve large and complex problems. In the new paradigm, adaptive encoding is still utilized as the basic representation. The objective variables will be initially divided into two parts. The first part includes the coordinates of all control points, while the second part consists of knot points. An initial population is generated for each of the two parts at the beginning of evolution. And then the two populations are evolved separately in a round-robin fashion, which means the current population will evolve for a predefined number of generations before activating the other one. For fitness evaluation, complete representation will be assembled with individuals from the active population and a representative from the unactivated population. The best individual so far is selected as the representative. CMA-ES [16] is adopted to evolve each of the two populations due to its excellent convergence feature with very limited number of fitness evaluations (FEs). The new algorithm is denoted as CMA-ES-CC. The advantages of CMA-ES-CC are apparent. It not only provides a platform to evolve both control points and knot vector(s), but also reduces the difficulty of TSDOPs by decomposing the objective vector into two smaller subcomponents (i.e., control points and knot vector). To evaluate the efficacy of CMA-ES-CC, experiments have been conducted based on two two-dimensional (2D) target shapes. The comparison with conventional EAs suggests that the proposed cooperative coevolution paradigm is very effective and efficient for TSDOPs.

The rest of this paper is organized as follows: Section 2 introduces the detailed formulation of TSDOP, which includes representation, fitness evaluation and related work. The drawbacks of existing evolution paradigms are also discussed in this part; Section 3 presents the proposed cooperative coevolution paradigm for TSDOPs; Section 4 provides the experimental studies based on two target shapes; Finally, Section 5 concludes this paper, and discusses a few directions for future work.

2. Target shape design optimization problem

As stated in Section 1, in this paper target shape design optimization problem (TSDOP) will be used as the miniature model of design optimization. The solution of TSDOP is to operate the designed shape to fit the given target shape. The basic components of TSDOP, which includes representation scheme and fitness evaluation method, will be described in this section. Related work on evolutionary approaches for tackling TSDOPs will also be reviewed briefly.

2.1. Representation

There are several shape parameterization techniques for shape representation and manipulation [17]. Due to the compact representation and a number of advantages, Non-Uniform Rational B-Splines (NURBS) are one of the most popular geometry