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Interactive truss design using Particle Swarm Optimization and NURBS curves

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ABSTRACT

This paper presents an interactive framework for the design of truss structures with incorporation of the subjective influence of user feedback in the design process. In the devised framework, the truss chords are described using Non-Uniform Rational Basis Splines (NURBS), a representation typically used in computer aided design (CAD) for describing free-form geometry. This allows for a convenient interface between the optimization scheme, namely a particle swarm optimizer (PSO), and the user. Based on the assumption that aesthetic design goals are not straightforwardly quantifiable, key elements for an interactive optimization framework are derived, and implemented for the design of truss structures subject to an additional set of structural criteria/constraints. Setting off from an initial design the user can visually assess interesting solutions that arise during the optimization process, save them for later assessment, actively drive the optimization towards individual goals, re-initialize the process from a set of preferred solutions, or restart the design. For translating the user's perception into quantifiable terms, a criterion is introduced to measure the similarity of candidate solutions with respect to reference designs. The framework is then applied in the design of 2D and 3D truss structures. The effectiveness of the similarity criteria, as well as the ability of the user to drive the optimization towards specific design goals is demonstrated.

1. Introduction

Structural optimization typically aims at achieving efficient structural performance while at the same time minimizing resources or material, commonly expressed via the minimization of structural weight, under a set of constraints, such as maximum allowed displacements and stresses, buckling behavior, and natural frequencies. Typical design variables include geometric parameters (positions, cross-sectional shapes, etc.), material parameters (strength, density, etc.) or topological parameters, e.g., material distribution. Furthermore, the structure to be optimized, as well as the design space, may be continuous, discrete or both [1,2].

Since the design space can be quite large, and the optimization problem may be non-convex (e.g., in topology optimization), population-based heuristic search optimization methods have been proposed and used successfully in such problems, thereby outperforming gradient-based methods. Rajan used a genetic algorithm (GA) to perform shape, sizing and topology optimization of truss structures [3]. Xie introduced (bi-directional) evolutionary structural optimization ((B)ESO) to perform topology optimization of continuous structures [4]. Bel Hadj Ali et al. have used a genetic algorithm based optimization scheme for the design of a tensegrity-based footbridge [5]. In previous work of the second author a GA optimization process was enforced for the optimal performance based design of frames based on a uniform damage criterion [6]. Coello Coello et al. utilized a similar scheme for optimal design of truss structures [7], and several other researchers have most commonly relied on the use of GAs as the heuristic tool for the structural optimization problem [8–11], or in general for multi-objective optimization in the early stages of an architectural design often with energy related objectives [12–15]. Other than GAs, which are fairly popular, several other heuristic approaches have been proposed for the solution of structural optimization problems [16–20], while often incorporating response behavior criteria [21,22].

In this paper, the Particle Swarm Optimization (PSO) method is implemented as the optimizer tool. This was introduced by Kennedy and Eberhart in 1995, and essentially works on the basis of mimicking the behavior of flocks or "swarms", searching for food or escaping a predator [23]. The interested reader is referred to [24] for an extensive review on successful applications of the PSO

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method. The advantages of PSO compared to the GA comprise a simpler setup, an often faster convergence rate, and computational efficiency, while still providing the same quality solutions [25]. Fourie and Groenwold were the first to apply the Particle Swarm Optimization (PSO) method for the design of truss structures, confirming its efficiency compared to GAs [26]. Since then, many variations of the algorithm, when applied to structural optimization, have been proposed and implemented [27–31]. Recently, hybrid algorithms have started to emerge, such as cellular automata and Particle Swarm Optimization [32].

Despite its wide applicability so far within the framework of structural optimization, little attention has been given to incorporate aesthetic, or more specifically, architectural criteria directly into the optimization process. In fact, mostly quantifiable, i.e., rather objective criteria, have been used. Shea assigned an aesthetic measure to truss structures based on the uniformity of their angles and the golden ratio [33]. Schein used volumetric constraints as architectural criteria in the optimization of a space frame by defining a volume in the structure that must not be crossed by members [34]. Pugnale optimized a continuous roof structure using the position of the columns as architectural constraints [35]. The inherent difficulty met in these approaches is that, in general, aesthetic criteria are highly subjective to the architect, and, therefore, not quantifiable [36]. Our use of the term architectural criteria reflects generally unquantifiable constraints, and is not implying that the potential user of our proposed method must be the architect. Rather, it refers to the potential actions of both the engineer and the architect, when however pertaining to the morphology of the structure. It is further noted that this method is particularly useful in the early, conceptual, stages of a design process as demonstrated by many successful cooperations between architects and engineers in the context of Switzerland [37].

On the other hand, capitalizing on the trial-and-evaluate characteristic of population type optimization methods, non-quantifiable objectives have been successfully achieved in interactive evolutionary computation for engineering and design applications [38–40]. An interactive genetic algorithm has been proposed by Von Buelow, allowing the user to make selections after each iteration, e.g., select parents to breed, mutate, or insert a new design into the process [41,42]. The algorithm has been successfully applied in the interactive design of a small truss bridge. Moreover, Hu and Eberhart recently analyzed the human–swarm interaction during the optimization process by means of a computer game, and concluded that the combination of computational power and human intuitive knowledge is advantageous for complex tasks [43]. Interactive PSO was introduced in 2005 [44], and only very few applications have been presented so far, including chemical engineering [44], and facial composite generations [45]. In this paper, the potential of the PSO is explored within the context of interactive architectural design subject to structural constraints. Our work is similar to [41] in that user interaction is incorporated in the design process. The difference, besides using PSO and not GA, is that, while in [41] the interaction is used to modify the behavior of the algorithm (selection, mutation, etc.), our work incorporates the design feedback as constraints into the algorithm. Another interactive design tool, which also uses genetic algorithms, is presented in [46,47]. Similar to [41], the user can select which designs are used to breed the next generation. In addition, the focus of the work in [46,47] is on speeding up the exploration process by developing a regression model of possible designs. In contrast, the focus of our work lies in capturing the intent of the designer and guiding the optimization process towards it.

A second aspect of the novel contribution of this work lies in the use of non-uniform rational basis-spline (NURBS) curves to describe parts of the structure. NURBS curves are a generalization of Bézier (b-) splines, and are, together with NURBS surfaces, widely used in computer-aided design (CAD) programs, due to the computationally efficient description of free-form geometry. In addition, employing the NURBS description allows us to use the initial architectural design as an initial configuration, and perform the optimization on these natural variables. Therefore, NURBS are ideal for describing problems of structural optimization with architectural freedom of design.

The introduced interactive PSO-based optimization process comprises a valuable tool for the architectural design of truss structures, further enabled via the use of NURBS for reducing computational complexity and favoring architectural freedom of design by allowing for free-form shapes that meet structural requirements. The value of the proposed framework is that it can be easily extended to account for more generic types of structural systems, such as for instance structural frameworks comprising beam and column elements. It is noted at this point that the choice of PSO as the optimizer tool was guided by the availability of a generic code that is easily adaptable to the introduced framework. However, any other meta-heuristic optimizer, e.g., the firefly or the bat algorithm [48], could be employed when appropriately calibrated.

This paper builds on the previous work of the authors [49]. The present paper includes the mathematical description of NURBS, and a discussion on and quantification of the advantages of NURBS. Further, the present paper includes a set of more realistic and architecturally more relevant examples, as well as an extension to 3D problems. Finally, in [49] the choice of the user is included in the objective function through an artificial weight reduction, whereas in this work, it is more formally incorporated via an updated similarity constraint.

The paper is organized as follows. Sections 2 and 3 detail the necessary background for NURBS and PSO, respectively. Then, Section 4 describes the proposed interactive algorithm. Section 5 illustrates its implementation on different design problems. Finally, Section 6 concludes the paper and discusses future research directions.

2. Non-Uniform Rational Basis Spline (NURBS)

2.1. Overview

The development of NURBS curves and surfaces was pioneered in the 1950s by the French engineers Bézier and Casteljau in their research for a sound mathematical description of free-form structures, in their case for car bodies. A complete description of NURBS curves is beyond the scope of this paper, and can be found in standard textbooks [50,51].

In brief, a NURBS curve $C(u)$ is described by its degree n, a set of weighted control points $\mathbf{P}_i$, $i = 0, \ldots, k$, and its knot vector. The control points may have any dimensionality; in the case of 3D representations they simply indicate a position in the 3D space. The knot vector discretizes the parametric space in intervals known as knot spans, which essentially constitute regions over which certain basis functions take effect. The values in the knot vector should be structured in nondecreasing order. A variable $u \in (0, 1)$ parameterizes the position of a point on the NURBS as [51]

$$C(u) = \frac{\sum_{i=0}^{k} q_i \mathbf{P}_i N_{i,n}(u)}{\sum_{i=0}^{k} q_i N_{i,n}(u)} = \sum_{i=0}^{k} \mathbf{P}_i R_{i,n}(u) \tag{1}$$

in which $q_i \in \Re$ are the weights, $N_{i,n}$ are normalized basis functions of degree n, and ultimately $R_{i,n}$ are the so-called rational basis