Multiobjective Shape Optimization Using Estimation Distribution Algorithms and Correlated Information

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Abstract. We propose a new approach for multiobjective shape optimization based on the estimation of probability distributions. The algorithm improves search space exploration by capturing landscape information into the probability distribution of the population. Correlation among design variables is also used for the computation of probability distributions. The algorithm uses finite element method to evaluate objective functions and constraints. We provide several design problems and we show Pareto front examples. The design goals are: minimum weight and minimum nodal displacement, without holes or unconnected elements in the structure.

1 Introduction

Shape optimization has been widely tackled by evolutionary algorithms. Genetic algorithms, (GAs), have been applied to shape optimization problems with some success, providing feasible solutions with acceptable fitness value [1, 3]. Nonetheless, GA based approaches present difficulties at finding solutions without holes or unconnected segments. This behavior can be explained by population diversity issues, which favor premature convergence and reduced search space exploration [2, 4].

In this paper, we present a multiobjective algorithm for shape optimization (MASO), which is based on estimation distribution concepts. The approach uses binary representation, and makes calls to an external finite element system to evaluate the fitness of candidate structures (individuals). MASO is related to univariate marginal distribution algorithms (UMDA) [6], and to Population Based Incremental Learning (PBIL) [7]. Therefore, every g generations, MASO estimates a (biased) probability distribution by sampling the current Pareto set. The new random population is generated with the updated distribution.

We have improved the algorithm's performance by using specific knowledge derived from the problem domain. This information, combined with the current Pareto set, provides better distribution estimations. Through experiments, we

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have observed enhanced exploration around promising areas, and less number of small holes and unconnected elements in the structure. Other approaches infer this relationship through the use of Bayesian probabilities [8, 9].

2 Problem Definition

The problem is to find the set of structures which fulfill design constraints (stress), and optimizes: total structure weight and, node displacement in one or more nodes (see Figure 1). Also, a minimum number of "objects or pieces" in the structure is desired. Another desired characteristic for the resulting structure is a minimum number of "small holes".

Fig. 1. Problem definition, initial search space and the minimum weight structure

In our problem, the design constraints are given by a maximum permissible Von Misses stress [10] (a standard criterion for mechanical design which represents the material resistance). The algorithm works on a delimited region (the whole piece) as it shown in Figure 1. The structure on the left side is the whole search region, that is, all structure's elements are present. The delivered design, shown on the right hand side, has minimum weight and minimum displacement (therefore, a member of the Pareto front). The design is achieved by "removing elements" from the structure, which is previously represented in discrete form for this purpose [11] (an "element" is one cell of the grid). Thus, binary representation is ad hoc for this problem. A "0" value represents a hole in the structure, while a "1" represents a given thickness value t. The discrete space and a representation example are shown in Figure 2.

3 Objective Functions and Constraints

As noted before, the design problem has two objective functions: the first objective is the minimization of the structure's weight, including the total number of "objects" needed to build the structure, and the number of "small holes". The