

Title:

Shape Optimization Definiteness using NURBS Curves and Genetic Algorithm

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Introduction:

Topology optimization (TO) tries to find the best distribution of materials inside a region of interest that meets certain desirable criteria fixed a priori. Although TO methods are effective in determining a good initial distribution of material in the design domain [4,6], they are cell-based representation of topology, which in many cases lead to irregular and vague boundary layouts. A post processing procedure is usually done to refine the results obtained and increase the efficiency of the TO layout. Many attempts for smoother and definite material boundary have been studied, most of them done by the parameterization of the TO initial distribution leading to Shape Optimization (SO) [3,5]. Shape Optimization is a process in which various methods are used to find the best geometric definitions of the boundaries found in the initial layout, while configurations such as holes and regions of different materials remain unchanged. Given the complexity of the task, SO are of great interest searching for the most fitted and optimized solution.

It is natural that a proper representation of the boundary shape is essential for efficient optimization. In order to obtain a flexible solution for the problem, NURBS are applied to define the sections of curves that form the internal boundary of the solutions obtained. In this work the parameterization process involves identifying the boundaries of different materials and defining these boundaries by NURBS curves. This approach conveys the ability to define the internal boundary profile to have more flexibility in handling the boundaries of the topologies in the parameterized model, and therefore to obtain an efficient SO. Once a parametrized model is defined, the shape optimization can be performed using the parameters of the boundary curves as the optimization variables. A Genetic Algorithm (GA) is used to optimize the best variables (control points and weights) for achieving the best coordinates of the boundary curves, sufficing a fitness function criteria.

Main Idea:

To aim at best SO results, we propose, to use the interpolation of an appropriate set vertices of the polygons that form the internal boundaries of the TO results. Two main difficulties were defined and solved: First, maintaining the topological characteristics of the layouts at the intersection point of these lines, avoiding regions of different materials. Which was solved by considering vertices at the outer edge of the design region and intersecting vertices of lines of the internal border always as initial or final points of the NURBS curves of each section. Second, maintaining the topology once lines at an intersection may intersect at weight parameters and control points are changed during the SO process. This was avoided by choosing appropriate ranges of values for the variables related to the coordinates of the control points and values of the weights.

A refinement of the grid of the discretized space is done before the parameterization of the boundary in order to have a suitable number of candidate points to become vertices and to make that two distinct vertices that will be chosen as extreme points in the NURBS are not extreme of the same edge. Next, an identification of the polygonal that forms the inner border of a solution, is done. Then, the vertices on the discretized design space are classified according to the number of edges belonging to the internal boundary that is linked to it. Each vertex is assigned a value 0, 1, 2, 3 or 4. Figure 1 presents an example of such classification. 1(a) represents a discretized design space; 1(b) Discretized design space with grid refinement and 1(c) Vertices classification matrix.

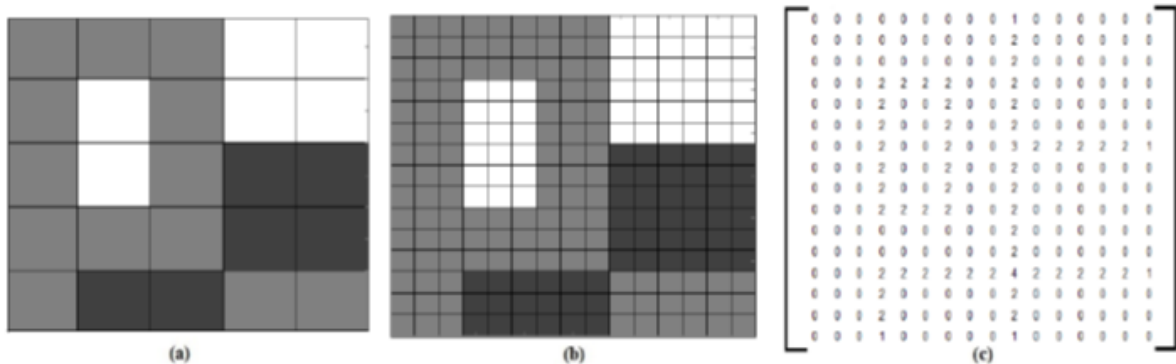


Fig. 1: (a) discretized design space; (b) Discretized design space with grid refinement; (c) Vertices classification matrix.

Figure 2 depicts a detailed classification of the vertices. Vertex X_0 has the value 0 because it is on the interior of a region. Those on the inner border are classified from 1 to 4: vertices classified as 1 are also over the external border of the design space what make that only one edge of the inner border is connected to him, as vertices X_1 , X_3 , X_5 , X_6 and X_7 ; vertices classified as 2 are those that belong to a line separating only two different material region, see vertex X_4 , in the same manner, vertex X_2 is assigned value 3.

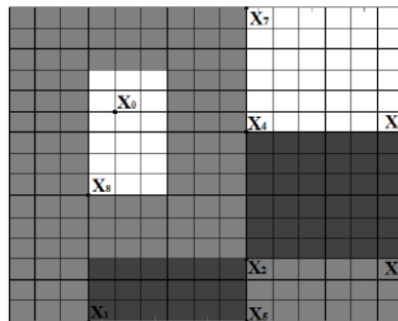


Fig. 2: Vertices Classification.

The NURBS curves that interpolate this set of points will be an approximating curve to the inner border. Starting from a vertex with classification 1, 3 or 4 the procedure search for the vertices connected to it by an edge in the inner boundary. Then choose one of them (not yet used) as the next vertex in the polygonal curve. The process continues selecting connected vertex by edge in the inner border until reaching to a vertex with classification 1, 3 or 4. The vertices are mapped into the

coordinates in the design space and then these set of selected vertices can be interpolated by a p -degree NURBS curve C_1 (see Fig. 3).

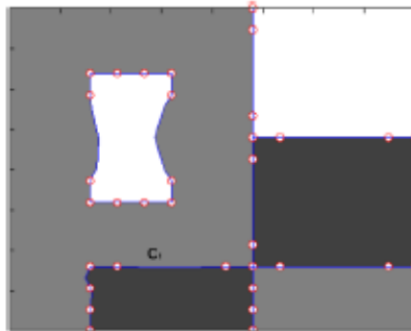


Fig. 3: Selected vertices of the polygonal on the inner border and its interpolated NURBS curves.

Shape optimization using GA:

The range of the variables associated to each control point coordinate was one third of the distance to the nearest control point. The suggested choices for the upper and lower bounds for weights and coordinates of the control points were able to maintain the topological properties of almost every layout found by the TO stage (not detailed in this paper) when applying GA for the shape optimization.

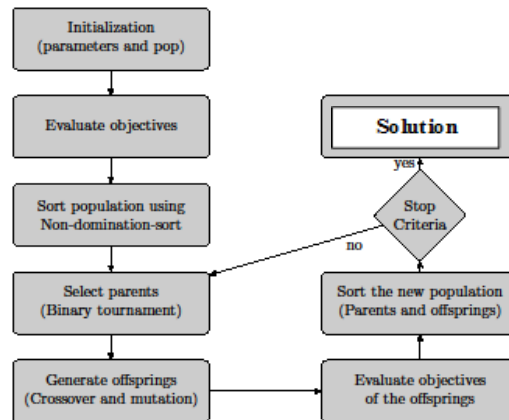


Fig. 4: Flow chart of the Genetic Algorithm used in this work.

The shape optimization of a parameterized solution is done by applying GA for optimizing the fitness function, (detailed in [2]). The process of GA used in this work is depicted in Figure 4. The GA parameters have the following values: Population size, $pop = 40$; Crossover rate 0.8; Pool size equal to half the population size; Number of generations $gen = 200$ (serves as stop criteria); The range of the weights variable was from 0 to 20; configured with binary tournament selection of the parents chromosome. The genotype (representation) is given by the coordinates of the control points and the weights of all the NURBS curves that describe its internal boundary.

The choice of the range of values allowed for the coordinates of the control points and the weights should be made in a way that the topological characteristics are preserved, that is, no new regions are created and the existing regions are maintained. The range defined for the coordinates of control points

takes into account the distance to the closest control point. The range for the weights is defined as a fixed range.

The proposed approach was applied to the study of the optimization of a C-core magnetic actuator [1]. The C-core magnetic actuator is composed of three main parts: the armature and the yoke solid blocks of ferromagnetic material; and the design domain, which was discretized into a square grid. Each cell within the design domain can assume three states, corresponding to three different materials: air, iron or a magnetic material (for this specific example, *NdFeB* magnets were used). The goal of the design of the c-core is to find an optimal material distribution that maximizes the *x-directional* attractive force F_x on the armature or equivalently minimizes the negative of this force, while minimizing the volume Vol_{PM} of permanent magnet material (PM) in the design region. The cost of the permanent magnet material is related to the volume of PM, and it accounts for the majority part of the cost of the device due to the high price.

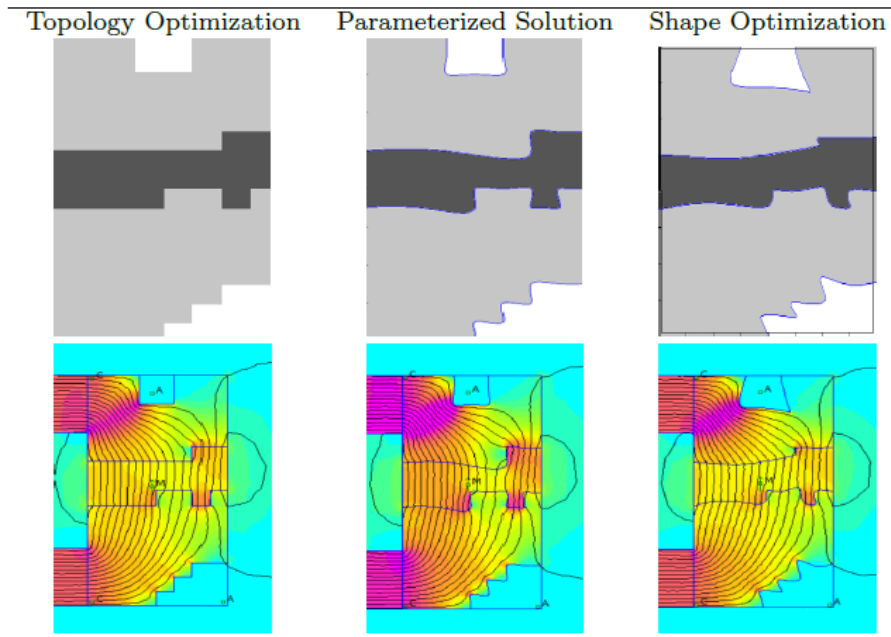


Fig. 5: Example one: Topology Optimization (left), Parameterization Solution (middle), Shape Optimization (right), the respective calculated field lines are presented respectively.

Figures 5 and 6 depict two examples of the design domain, tested for different topologies obtained. Both Examples have the same objectives functions as detailed above but the, the weights representing the values of importance differ. Each of the figures contains six figures divided to Topology Optimization, parameterization, and Shape Optimization. For each one of the stages the field force lines are indicated, showing the progressive features and results through the whole process.

Conclusions:

This work presents an integrated approach of an automated multi-material process of SO using a parameterization process, applied to the results found in the TO stage. Using NURBS curves and GA optimization, conveyed leading to a refine tuning of the internal boundaries separating regions of different materials. The experiments show the adequacy and edibility of the proposed method.

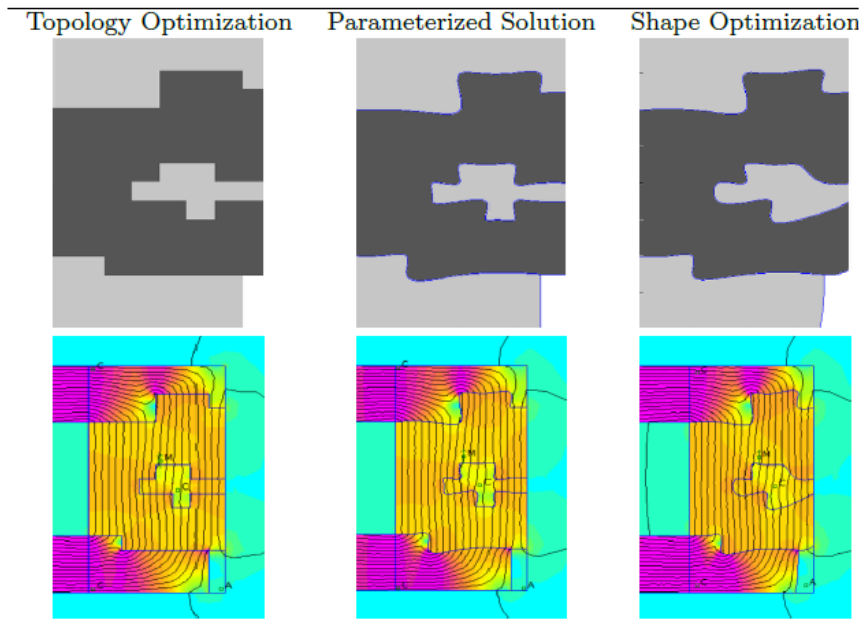


Fig. 6: Example two: Topology Optimization (left), Parameterization Solution (middle), Shape Optimization (right), the respective calculated field lines are presented respectively.

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