An application of hierarchical chromosome based genetic algorithm to the optimization of platform shape.

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Abstract. In this paper we present hierarchical chromosome based genetic algorithm and its application to solving of exemplary design problem - optimization of platform shape. The problem consists in finding the optimal shape of the platform with minimal overall volume and the stress value not greater then the maximum admissible value, when the platform is under the external load. The algorithm uses hierarchical chromosome representation and hierarchical genetic operators, instead of the binary representation and traditional genetic operators. It allows for coding of phenotypes with different number of components as well as performing reproduction with such individuals. In order to solve the problem, the application with hierarchical chromosome based genetic algorithm was interfaced with the parallel fully automatic hp adaptive 3D Finite Element Method package (*parhp3D).* The *parhp3D* application was used to compute the stress values for individuals generated by genetic algorithm.

1 Introduction

Hierarchical structures are very often used as object representation in many evolutionary algorithms. For design system based on evolutionary algorithms the representation has big advantage: it allows to code artifact with different number of components as well as to code relations between components. Thus the design systems with hierarchical structure based evolutionary algorithms can solve design problem even if the optimal number of artifact components is not known. The examples of such a design systems are graph-based genetic algorithm and hierarchical chromosome based genetic algorithm [1, 4, 5, 7]. The paper presents hierarchical chromosome based genetic algorithm and its application to optimization of platforms shape. In order to compute the stress values for individuals (platforms) generated by genetic algorithm, the application with hierarchical chromosome based genetic algorithm is interfaced with the parallel fully automatic hp adaptive 3D Finite Element Method package [6].
The paper is organized as follows. In the following section a phenotype representation – Clipped Stretched Cubes representation - is described. Then the hierarchical chromosome based genetic algorithm used to generate 3D-solids designs in a CAD system is presented. In the next section an application of hierarchical chromosome based genetic algorithms to the optimization of platform shape is presented. Some conclusions are summarized in the last section.

2 A phenotype representation – the Clipped Stretched Cubes Representation

Object representation [3] - in the paper called artifact or phenotypes - is one of the most important elements of any design system. The definition of phenotypes representation defines also the space of solutions generated by the system. The representation influences the size and the complexity of genotypes, because each phenotype has corresponding genotype. The phenotypes described in the paper will be 3D objects. In most cases the genetic algorithm optimizes only chosen parameters. Our system should be able to modify all parts of an object. The solid representation should be defined in such a way, that the genetic algorithm based system will be effective. Application of genetic algorithm to the designs generation enforces many constraints on representation of phenotypes [1]. Representation, which describes designed objects by listing its verticles, requires big number of parameters for defining even the easiest shapes. Large number of parameters in the phenotype causes large number of genes in the genotype. Thus finding of the solution will be more difficult .The representation should describe the shape in the exact way by utilizing minimal number of parameters. The representation should also enable easy shape modification. The representation, which locates similar objects closely in the search space, makes the genetic algorithm able to find the evolutionary path from the worse objects to the better ones.
In this paper the Clipped Stretched Cubes representation (CSC) is used. The solid is defined by partitioning into a number of not intersecting primitives. The primitives are represented as cubes, eventually clipped by a plane and stretched in some direction – see Fig.1 and 2.

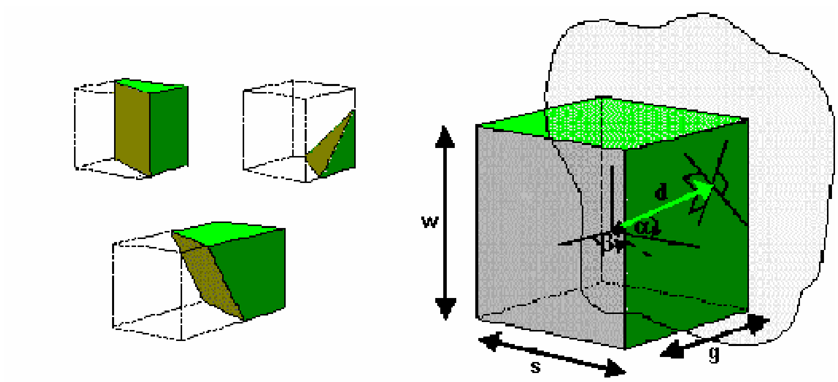

Figure 1. Exemplary primitives and primitive with denoted parameters.

Each primitive is described by nine following parameters:
1-3. Coordinates of the cube center (x, y, z).
4. Height *w*.
5. Width *s*.
6. Depth g.
7-9. Parameters defining the clipping plane – angles α, β, and the distance *d* of the clipping plane from the cube center.

Figure 2. Exemplary objects and its primitives.

3 Hierarchical chromosome based genetic algorithm

Once we have selected the most suitable representation, we need to introduce the phenotype coding. In our work the CSC representation is used as a phenotype representation. Thus each phenotype consists of a number of primitives and each primitive is described by nine parameters. For phenotype coding, the hierarchical chromosome is used. Fig 3 presents an artifact and the corresponding genotype (hierarchical chromosome).

The hierarchical mutation and hierarchical crossover is used to generate offspring from artifacts coded as hierarchical chromosomes. Two kinds of hierarchical mutation are used: the mutation of alleles and the mutation of groups of alleles. Mutation of alleles corresponds to traditionally mutation of binary strings. Mutation of group of alleles (coded primitive) allows to add or remove the whole primitive from the genotype. This genetic operator is responsible for changing of the phenotypes length.

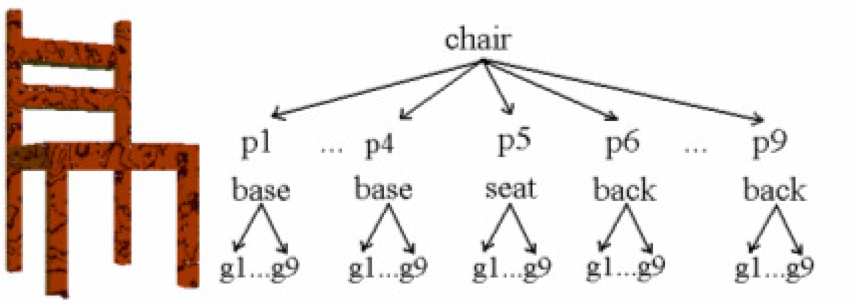

Figure 3. An artifact and corresponding hierarchical chromosome.

The algorithm for mutation of the group of alleles is the following:

- randomly choose the group of alleles (a primitive) in the hierarchical chromosome,
- randomly decide, if it should be removed or split,
- if removing was chosen, then remove the whole group of genes from the chromosome,
- if splitting was chosen then:
    - randomly chose the clipping plane,
    - calculate the new value for each allele from the primitive and for each allele from the newly created primitive,
    - add new group of alleles to the hierarchical chromosome.

Fig. 4. a) presents a phenotype before mutation. Fig. 4. b) presents the phenotype after removing the primitive. Fig 4. c) presents the phenotype after splitting of the primitive.

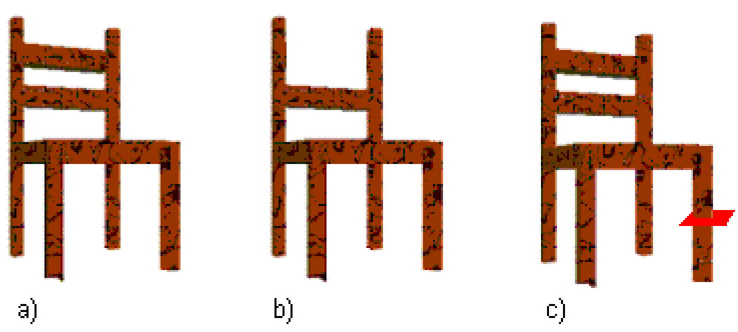

Figure 4. Exemplary phenotypes before and after mutation.

Mutation of previously split phenotype, may result in changing of the newly created primitive. Fig. 5 a) presents a phenotype before mutation. Fig. 5. b) presents the phenotype after primitive splitting, and Fig. 5. c) presents the phenotype after mutation of alleles.

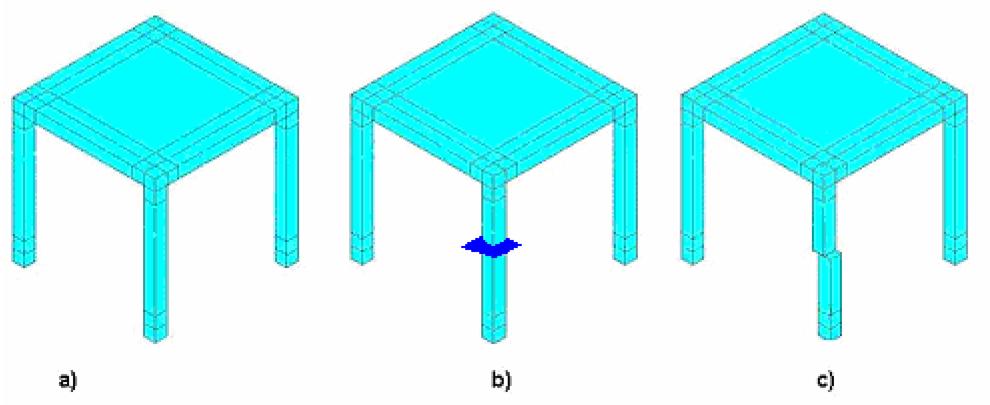

Figure 5. Exemplary phenotype before and after mutation.

The next used genetic operator is the hierarchical crossover [7, 8]. The hierarchical crossover is the two stage process, which consist in:

- finding the suitable crossover point in the parent individuals,
- applying the crossover to the offspring generating.

In the one-point crossover the similarity point is the randomly chosen bit. For the hierarchical crossover the step is more complex. The similarity point is (P_1, P_2, g, b), where P_1 is the number of the primitive in the first parent, P_2 is the number of the primitive in the second parent, g is the gene number, and b is the bit number.

The second step consists of copying all the primitives located left from P_1 or P_2 and their sub-trees to the children being generated – respectively, from the first parent to the first child, from the second parent to the second child. Then the process of copying of verticles and its sub-trees is repeated on the next level until the vertex g. For vertex g the one point crossover with crossover point b is used. Then all verticles on the level of the genes located right from g with the ancestor P_1 or P_2 are copied from the first patent to the second child and from the second parent to the first child. After that all primitives located right from $P1$ or $P2$ and their sub-trees are copied to the children – from the first parent to the second child, from the second parent to the first child.

4 Application of hierarchical chromosome based genetic algorithms to the optimization of platform shape.

Hierarchical chromosome based genetic algorithm can be used in design problems, in which the optimal number of object components is not known. The algorithm is utilized to solve the problem of finding the optimal platform shape. The problem consist in finding the optimal shape of the platform with minimal overall volume and the stress value not greater then the maximum admissible value, when the platform is under the external load. The optimal shape of the platform is found by changing number, location and shape of the components of the platform.

An example of a phenotype modeling the platform is presented in Fig. 6.

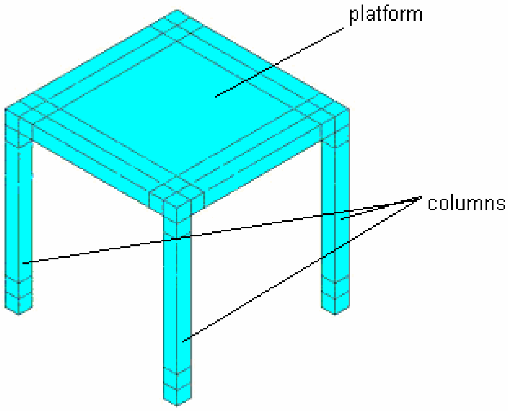

Figure 6. An example of a phenotype (platform).

The cross-section of the platform has dimensions 100×100 cm. The height of the platform and the size of cross-sectional dimensions of all columns and their location are optimized by the genetic algorithm.
The stress distribution in the modeled area is described by the linear elasticity equation:

$$\sum_{j=1}^{3} \frac{\partial \sigma_{ij}}{\partial x_j} = 0 \tag{1}$$

where σ_{ij} denotes the stress tensor defined according to the following rule:

$$\sigma_{ij} = 2\mu\varepsilon_{ij} + \lambda\delta_{ij}\varepsilon_{kk} \tag{2}$$

In equation (2) ε_{ij} denotes the strain tensor defined by the partial derivatives of the displacement vector field u_i.

$$\varepsilon_{ij} = 0.5\left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i}\right) \tag{3}$$

μ and λ are Lame coefficients:

$$\mu = \frac{E}{2(1+\nu)}\,;\, \lambda = \frac{\nu E}{1+\nu} \tag{4}$$

Coefficients μ and λ depend on the Young modulus E and Poisson ratio ν. Young modulus and Poisson ratio define the platform material parameters. In our example we consider a platform made from the carbon constructional, high-quality, general–purpose steel with the Young modulus and Poisson ratio equal to $E = 206 * 10^9$ [Pa] and $\nu = 0.3$.
The assumed boundary conditions are presented in Fig. 7. We assume, that columns are attached to the floor. It implies Dirichlet boundary condition:

$$u_i = 0 \; on \; \Gamma_D \tag{5}$$

where Γ_D represents the bottom of the columns. The central part of the platform, denoted with the red stripped rectangle, was loaded with the force $g = 30$ kN, directed in the direction of (0, -45^0, 0). This is modeled by the Neumann boundary condition:

$$\sigma_{i,j} \circ n_j = g_i \text{ on } \Gamma_N\,; \tag{6}$$

where Γ_N represents the central part of the platform.
The Finite Element Method (FEM) [2] was utilized to solve the equation (1) with the boundary conditions (5), (6). The genetic algorithm with the hierarchical chromosome based application was connected with the parallel fully automatic hp adaptive 3D Finite Element Method application [6]. Presented here results were obtained after 50 iterations, starting from an initial population consisting of 50 individuals. Fig. 8. a) presents the best obtained individual.
The platform components with the biggest stress: the central components and the components with attached columns have the largest thickness. Columns with the largest stress have components with largest cross-section. Fig. 8. b) presents the stress distribution over the individual presented in Fig. 8.a). From the obtained results it follow, that the increase of the cross-sectional area of the most loaded parts of columns is necessary to prevent horizontal bending of the columns.

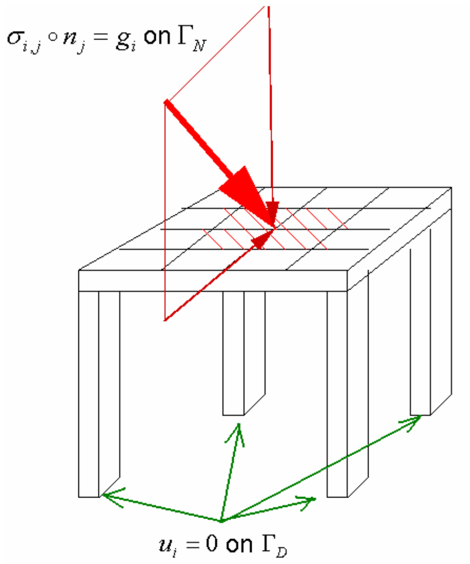

Figure 7. Boundary conditions

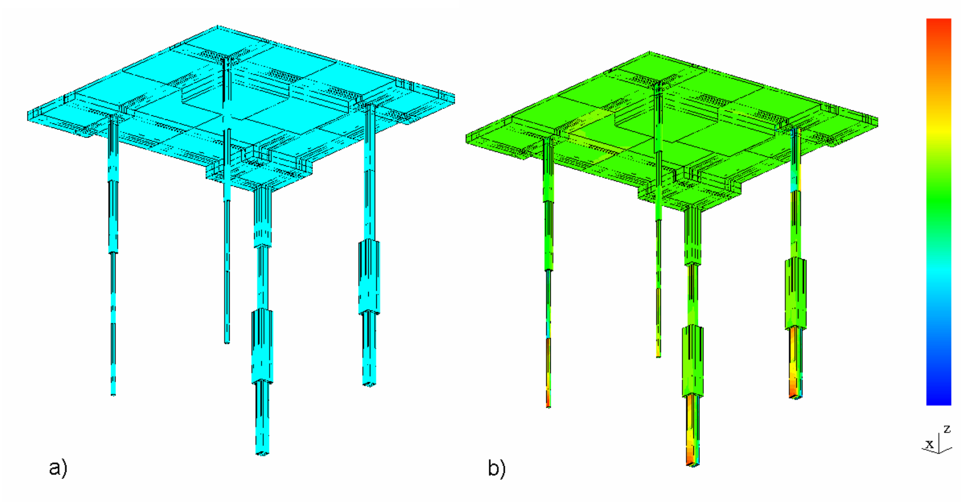

Figure 8. The best individual and its stress distribution

5 Conclusions

In this paper the hierarchical chromosome based genetic algorithms was presented. The algorithm, thanks to hierarchical chromosome representation and hierarchical genetic operators, allows for finding the solution even in the situation, when the optimal number of components of solution is not known. The hierarchical chromosome based genetic algorithm was used for solving exemplary design problem - finding the optimal shape of the platform with minimal overall volume and the stress value not greater then the maximum admissible value, when the platform was under the external load. In order to compute the stress values for individuals generated by genetic algorithm, the application with hierarchical chromosome based genetic algorithm was interfaced with the parallel fully automatic hp adaptive 3D Finite Element Method package. The best obtained individual, as well as its stress distribution were presented in the paper. Presented hierarchical chromosome based genetic algorithm can be used in many other optimization problems, especially design problems, in which very often the number of components is not known. The future work will involve solving of more complex design problems. Our research will also concentrate on relating the known stress distribution to probability of local modification of the objects.

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