An Approach to the Interactive Design Process Using Genetic Algorithms

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ABSTRACT

This paper is aiming to apply the Genetic Algorithms (GAs) to the interactive design. For that purpose, the scheme for utilizing the past design processes for the next interactive design process is proposed. In this scheme, the process consists of three phases: the searching phase, the tuning phase and the design phase. The first phase searches the optimal decision sequences for the past design instances by GAs. By the collected sequences, the second phase tunes the criteria of selecting decision sequences for the next design process. By this scheme, the implicit constraints satisfied in the past design can be applied to the next design. Finally, the computer simulations on the simple gear-train design were carried out to show the effectiveness of the scheme.

INTRODUCTION

The design in industry, a highly intelligent activity of human, has been aided or partially automated in the framework of CAD. In that, the techniques grown in the field of Artificial Intelligence (AI), e.g., the inference mechanisms, the learning algorithms, and the expert system take the leading part. As well as them, an important basics in AI is the searching techniques.

One of them, the Genetic Algorithms (GAs)[1] developed by Holland, et al. have been highlighted in recent years. The algorithms mimic the natural evolution process and utilize its adaptability to the environment. Then it features the problem-independency of searching, intrinsic parallelism, the flexibility of problem representation and so on.

Here, we try to apply such algorithms to the interactive design process, especially to the local constraint propagation method for the constraint maintenance problem. In the process, GAs are used to search the optimal design-modification sequences which are utilized to tune the parameters for improving the later interactive processes.

First, we discuss about the constraint propagation method adopted here, and then describe the design process incorporating the GAs. After that, we demonstrate the effectiveness of our scheme by the experiment with computer. In it, we use the problem of the simplified gear-train design as an example, and show the result.

LOCAL CONSTRAINT PROPAGATION METHOD

Though the interactive phase can be seen in each subprocess of design, we restrict the object to the parametric design process. The parametric design, in general, is categorized into the two problems: The one is the global optimization which searches a set of parameter values that maximize the given objective function. And the other is the constraint maintenance which finds a set of parameter values that satisfies all the constraints between them when one of the values is modified.

Furthermore, the constraint maintenance problem is classified into the two categories by the solving methods: the global constraint solving and the local constraint propagation[2]. The former deals with all the constraints at one time, while the latter sequentially applies the rules and each of them modifies a parameter value to make it satisfy only one or a few constraints at a time.

The global optimization for the parametric design is the typical combinatorial optimization problem and a number of studies on solving such design problems by the GAs are reported[3]. Likewise, the global constraint solving can be considered to result in the kind of problem. Therefore we adopt the local constraint propagation as an object and apply the GAs to improve it.

The process of local constraint propagation method is described as follows: When a value of the design parameter is modified by the designer, some or all of the other parameters should be modified together to satisfy all the constraints between them. In this method, as mentioned above, a single rule to satisfy the violated constraint is selected according to a certain criterion and applied. This is repeated until all the constraints are satisfied. After that, a sequence of applied rules which we call the decision sequence is acquired. It is denoted by

$$SD = (d_1, d_2, \dots , d_i, \dots , d_L), \tag{1}$$

where $d_i \in \{c, r\}$, c represents the violated constraint and r is the rule which satisfies the constraint. Our aim is to improve such decision sequences. The proposed scheme for it is described below.

THE SCHEME

Usually, the local constraint propagation method are used for the interactive design with the large-scale constraint maintenance problem in which all the constraints can not be dealt with at one time. Therefore the method requires the quick response in the first place, and then in general the rule decisions are based on the heuristically acquired decision criteria which cost little time. Although these criteria are constant in the process, it is considered that they are not necessarily invariant during the process, or rather should be modified according to the past successful processes. Then we propose the scheme to modify the criteria by the preceding design processes[4]. Our scheme consists of three phases: the searching, the tuning and the design phases. It is conceptually illustrated in Fig. 1 and the detail is given below.

During the searching phase, GAs search the optimal decision sequences from the initial design to the reference design completed by the designer previously. As the measure of good sequences, i.e., the fitness function in GAs, we can adopt the length of the sequence, the number of the improperly adopted rules, etc. Thus this phase finds, for example, the shortest sequences which complete the imperfect modifications of the design. By using the searched sequences, the parameters of the criteria for selecting the rules are tuned in the tuning phase. As the criteria, the priority of each rule in the selection, invariability of each variable, the priority of each constraint, and etc. can be used. In the design phase, taking the partially modified design as the initial state, the rules are selected in turn according to the parameters tuned in the preceding phase, and finally all the constraints are satisfied, which is the final state.

By this three-phased scheme, it can be considered that the decisions of the rule selection improves as the decisions of the similar designs are repeatedly experienced. Furthermore, the implicit constraints involved in the past design can be acquired in the form of the parameters of the criteria and applied to the modifications in the next design phases.

THE SIMULATION

This section describes about the simulation on the proposed scheme, in which the simplified gear-train design problem is adopted as an example.

Gear-train problem

Here, we briefly describe the design of a gear-train system of double-speed reduction. Its schematic view

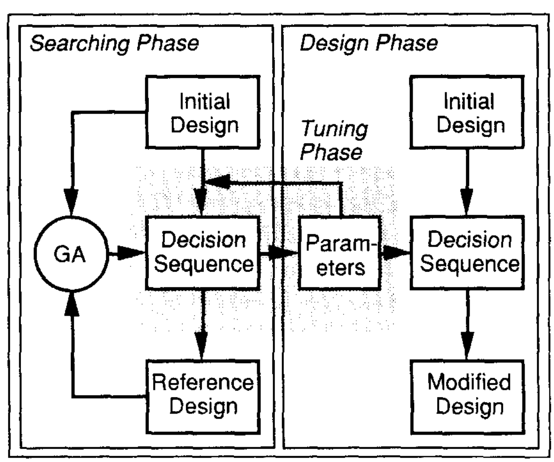

Fig. 1 Schema of interactive design process incorporating GAs.

is given in Fig. 2.

In the train, two pairs of pinion and wheel are included, the pinion on the output side (suffixed with 3 in the figure) is attached on the axis of the wheel on the input side (2), and the axis of the output wheel (4) is in line with that of the input pinion (1), i.e., coaxial. In the practical gear-train design, many variables on strength, contact and etc. should be considered. However, the problem here is fairly simplified. It has six variables: the four tooth numbers ($z_i\,; i = 1, \dots, 4$) and a pair of center distances (cd_{12} and cd_{34}). Between them, the six constraints (C_i ; $i = 1, \dots, 6$) are given to form the specified configuration. They are listed in Fig. 3 with some constant values appeared in the equations.

Here to do is improving the process of modifications which follows the incomplete, partial modifications made by the designer.

Searching by GAs

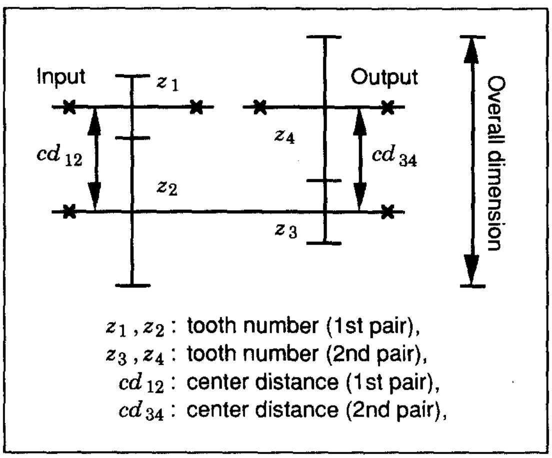

Fig. 2 Schema of coaxial, double-speed reduction gear train.

$$z_1 - 14 \geq 0 \cdots C_1\,,\; z_1 - 14 \geq 0 \cdots C_2$$

$$cd_1 = \frac{z_1 + z_2}{2} m_{12} \cdots C_3\,,\; cd_2 = \frac{z_3 + z_4}{2} m_{34} \cdots C_4$$

$$\left| \frac{z_2 \cdot z_4}{z_1 \cdot z_3} - r \right| \leq t_r \cdots C_5\,,\; \left| cd_{12} - cd_{34} \right| \leq t_a \cdots C_6$$

m_{12} : module (1st pair),
m_{34} : module (2nd pair),
r : transmission ratio,
t_r : tolerance of trans. ratio,
t_a : tolerance of center dist.

Fig. 3 Constraints between the variables.

First, a set of pairs of design instances are given. Each pair is composed of the initial design and the reference design, The former violates one or some constraints out of the 6, in other words, it is the incomplete modification. The latter stands for the desired design, the completely modified version of the corresponding initial design, which meets all the 6 constraints.

From such pairs of design instances, the first phase searches the decision sequences and stores them. To search the optimal decision sequences by GAs, we encode them as:

$$string = c_1\, r_1\, c_2\, r_2 \dots c_L\, r_L\,, \tag{2}$$

where $c_i \in \{ 1, \dots, n_c \}$, $r_i \in \{ 1, \dots, n_r \}$, n_c and n_r represent the number of constraints and rules included in the design respectively, and L indicates the maximum number of the steps of applying rules.

The fitness function for GAs is set as the next equation:

$$f = \frac{a_0}{\sum_{i}^{n_g} a_i\, g_i + a_{n_g + 1}} \tag{3}$$

where a_i ($i = 0, \dots, n_{g+1}$) represents the constant coefficient and $g_i (i = 1, \dots, n_g)$ represents the function which returns the goodness of the sequence. As the measure of goodness, or rather the badness, this experiment adopts the four indices ($n_g = 4$) : (1) the number of steps until all the constraints are satisfied, i.e., the length of the sequence, (2) the number of the violated constraints, (3) the number of the searched variables which are not agree with the corresponding ones of the reference design, and (4) the number of the unnecessarily applied rules.

For the genetic operators, the point mutation, and the 2-point crossover are chosen. Other specifications for the most part conform to the Holland's traditional GAs.

Use of searched sequences

The collection of the searched decision sequences is used to tune the criteria for the rule selection. Then the criteria are used to direct the next design phase. As such criteria, we can use the items listed in the previous section. But here, we restrict them to the simplest one, the priority of each rule in the selection. The priority here is given as the transitional probability, i.e., the conditional probability denoted by $P(r_{i+1} | r_i)$, which is calculated using the searched sequences.

The result

Fig. 4 illustrates the transitional probability calculated from the 25 decision sequences acquired by the 6 pairs of initial and reference designs. The height of each column represents the conditional probability of occurrences of the rule r_{i+1} under the condition that the rule r_i was applied just before. Fig. 5 shows the result of the design phase directed by the acquired transitional probability. The horizontal axis represents the number of the steps in the modifications, i.e., the length of the decision sequences, and the vertical axis represents the rate

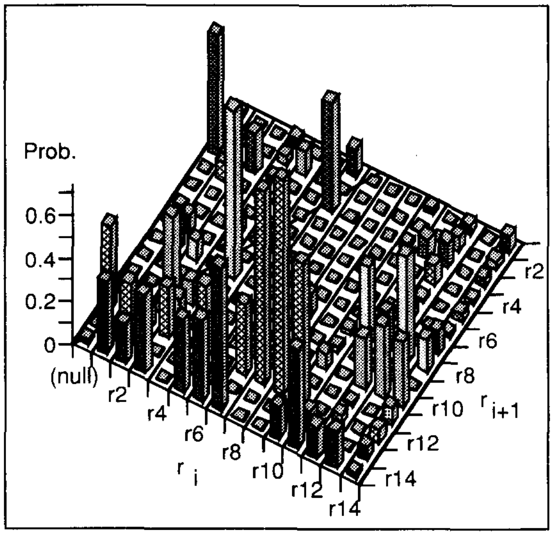

Fig. 4 Transition Probabilities calculated by the decision sequences.

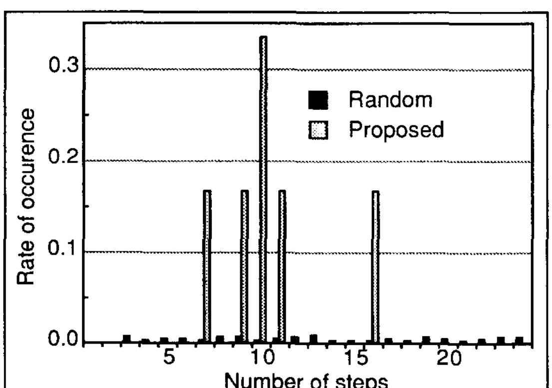

Fig. 5 Decision sequences made in the design phase directed by the transitional probability.

of occurrences of the sequences which have the given lengths. The grayed bars indicate the result by the proposed method and the black ones represent the result by the random method in which the rules are chosen randomly from the candidates. The steps over 25 is omitted from the graph. Because the most of the sequences by random exceeds the 30 steps, although the proposed method found no shortest sequences in this case, the proposed method is considered to be effective.

CONCLUSIONS

An approach to the improvement of the local constraint propagation method for the interactive parametric design has been presented and its effectiveness has demonstrated by the experiment with the simplified gear-train design.

The proposed method features the searching of the optimal decision sequences for the past design instances, and the tuning of the criteria for the future rule selection by using the searched sequences. This scheme makes it possible to extract the implicit constraints embedded in the past design and apply to the future design.

The problem adopted here may be categorized into the planning problem, and many planning method has been reported for a variety of applications. Among them, the proposed method has a lot to be refined. One of them concerns the strategy acquisition, which corresponds to the tuning phase of our method. In spite that the proposed scheme looks rather off-lined, it should incorporates some real-time learning algorithm. And the success of such modification will make it adapt the rapid change of the desired design.

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