Integration of Multi-objective and Interactive Genetic Algorithms and its Application to Animation Design

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Abstract

Interactive GA (IGA) is one of the methods solving decision-making problems that computer cannot evaluate solutions directly. The method forces the users to evaluate all the solutions generated by the computer. Hence it is difficult to solve practical problems only using IGA because the user must evaluate a great number of solutions, and more sophisticated assistance by computer is needed. This paper considers problems whose solutions can be evaluated by the computer partially. We propose an IGA to reduce number of evaluations by the users, enhanced by techniques such as multi-objective optimization and clustering. The proposed method is applied to a problem of generating animation of a pass-motion by hands so as to confirm usefulness of the method. Results of the experiments show that the proposed method can generate high quality solution with fewer stresses on the users.

1. Introduction

To design human like motions in animation by computer graphics is a difficult task. Currently, motions are designed by the designers directly or obtained by the motion capturing technique from motions of real humans. The former method allows flexibility in designing arbitrary motion, but at the same time, it is a very time-consuming job for the designers. Contrary to this, the latter method enables to obtain natural motions with small effort, but in the method, flexibility in the geometry of figures and tasks that the motions represent is limited. Thus, it is required to generate human like motions automatically or at least with small number of interactions with the designers.

Recent development in brain science and robotics gave sophisticated understanding of human motion planning. There have proposed several hypotheses that natural human motions are described by solutions of optimization problems of some evaluation functions [2]. Further, recent development of meta-heuristics such as genetic algorithms makes optimization of complicated non-linear functions possible [3]. Taking these factors into consideration, application of optimization techniques can be a promising approach to this problem. However, such criteria don't fully specify the motions and their remains some freedoms in motion. Hence, particular motion should be chosen by designers based on their subjective evaluation.

Another approach is the interactive genetic algorithms (IGA) , or interactive evolutionary computation (IEC) [8]. In IGA, the computer generates and presents alternatives applying crossover and mutation to current population of solutions. Then, the human evaluates and selects the survivors based on his or her preference. Thus, solutions of a problem whose evaluation function is difficult to describe explicitly as a computer program can be obtained by the IGA. However, in practical applications having many constraints, number of evaluation by human tends to be large only even to find feasible solutions. Further, in cases that solutions are temporal patterns such as animation, evaluation of many solutions by human becomes a very difficult task, and some devices for presenting solutions are needed.

In the present paper, the authors proposes an approach of integrating the multi-objective GA [9] and the IGA so as to take subjective factors into consideration and reduce the number of evaluations by the human. The proposed method is applied to a problem of generating animation of a pass-motion of two hands so as to confirm usefulness of the method.

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2. Problem of Animation Generation

2.1. Target Animation

This paper considers path-planning problems of human-like motions of link mechanisms. The purpose of the motions is to pass a small object from the right side hand to the left side hand.

Two link mechanisms are considered as subjects: Model1: The first subject is a 3-dimensional 16-joint link mechanism imitating the upper half part of the human body as shown in Fig.1. Model2: The second subject is a plane 4-joint link mechanism, which is a simplified model of the arms of the human body. See Fig.2. Every link is assumed to be a rigid body. The links are joined by revolute joint each other. Trajectory of the link is represented by a set of B-Spline functions, each of which represents the change of joint angle over time.

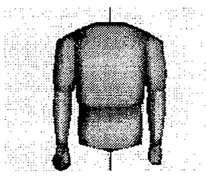

Fig. 1:The link of upper half of human body.

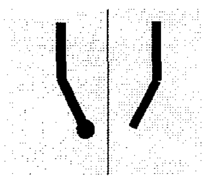

Fig. 2:The plane link of the both arms of human body.

At the start and the end, the link mechanisms stand still with the prespecified poses appropriate for the task. The both hands should touch each other at least once on the way of the path to pass the object.

The following constraints on motions are introduced.

(1) Physical constraints

(1-a)Joint angles must not exceed their prespecified limits.

(1-b)Joint torques must not exceed their prespecified maxima.

(1-c)All the links must not collide each other.

The following evaluation functions are considered so as to achieve natural motion from the viewpoint of dynamics.

(2) Evaluation of Pass-motion

(2-a) Small change of the joint torques are preferred [2].

(2-b) Small joint torques are preferred.

(2-c) Small acceleration of the handled object is preferred.

(2-d) Short completion time of the motion is preferred.

Accordingly the problem of path-planning can be formulated as a constrained multi-objective optimization problem with the control points of the spline functions as decision variables, with the items (1-a) through (1-c) as constraints, and with the items (2-a) through (2-d) as objective functions.

2.2. Characteristics of the Target Problem

(1) Existence of multiple criteria

As stated in the previous section, the target problem has several criteria. Currently, many optimization methods can not solve directly the multi-objective problems, and treat them by converting the multiple objectives into a single one. However, no established way for conversion is available, and therefore adjustment through trial and error is required.

(2) Existence of constraints

Constraints of the application are represented by a complex functions of decision variables. It is, therefore, difficult to generate feasible solutions in advance. To satisfy the constraints in optimization is required.

(3) Existence of Subjective Evaluation

Criteria described in Section 2 are merely partial criteria to be taken into consideration. Users seem to have other criteria besides those explicitly described in Section 2, and therefore subjective factor should be treated in deciding the path.

2.3. Existing Approaches and Discussion

2.3.1. Multi-objective optimization methods

The multi-objective optimization is a technique to treat the multi-objective problem directly without converting criteria into one. First, the multi-objective optimization methods generate a set of reasonable solutions called the Pareto optimal set. Then, the users select preferred solution in the set.

As preliminary study, we applied a multi-objective genetic algorithm into the path-planning problem. The real number vector representation was used in coding. Individuals are represented by a vector consisting of the spline control point. The unimodal normal distribution crossover (UNDX) was used as crossover [3]. Constraints were treated by penalty terms. Pareto optimal selection strategy (POSS) that preserves non-dominated solutions as survivors in the next generation and extinguishes the other dominated solutions was used to obtain the Pareto optimal solutions [4].

For the experiment, Model 1 shown in Fig. 1 was used. Used parameter are as follows: the division number of spline is 3, a number of crossovers in POSS is 10, the size of initial population is 200, maximal generation is 3000, the number of decision variables is 48, the number of objective functions is 6. Fig. 3 shows some of the obtained solutions.

Since in the POSS, all the non-dominated solutions are preserved, the number of individuals in the final population got quite large. After 3000 generations, approximately 2500 individuals remained. It is due to the nature that Pareto optimal solutions are infinite in multi-objective optimization problem of continuance variable. In such case, the POSS faces difficulty of growing population. Further, as shown in Fig. 3, the individuals included by the population in a trial resembled each other. It is also observed that the obtained solutions are quite different by trial.

Accordingly,

- Obtained Pareto optimal set includes very large number of individuals resembling mutually. Hence, some devices for selecting solutions should be needed to inquire the preference of the users.
- Obtained solutions change by trial. It means that necessary diversity is lost during search. Diversity of alternatives in decision variable space should be maintained so as to cover the whole Pareto optimal set well in one trial.

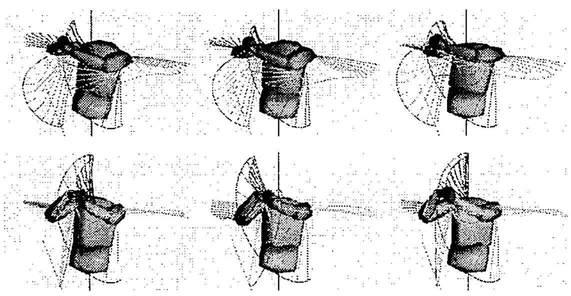

Fig. 3:The similar solutions obtained by the multi-objective GA. (3 individuals from each 2 trials)

2.3.2. Interactive Genetic Algorithm

Interactive genetic algorithm (IGA) is one of the methods to solve a problem whose evaluation function contains subjective factor of the users. In this section, we applied IGA into the path-planning problem as preliminary study, and discuss the results.

IGA is one of the methods intended to combine the global search ability of GA and thc evaluation by human. Basic algorithm of IGA is as follows:

(1) Computer generates some individuals as initial population.
(2) Computer mates the individuals and generates the new individuals as children by applying crossover or mutation. Then, they are presented to the user.
(3) User evaluates individuals proposed by the computer.
(4) Based on evaluation by the user, computer selects the individuals as survivors in the next generation.
(5) Go back to (2) until terminal condition is satisfied.

IGA can be applied to problems whose evaluation function is difficult to describe explicitly as computer programs because the users evaluate the solutions by themselves.

In the preliminary experiment, the same way as that in the multi-objective optimization was used as cording/crossover (2.3.1). Roulette wheel selection was used as selection of parent-individual for crossover. Figure 4 shows one example of solutions presented to the users by IGA.

As shown in Fig. 4, many infeasible solutions are presented to the users. That is, the arms collided, the joints bend over its range, passing the object was unsuccessful in some of the solutions.

Summarizing to the result, we must consider the following points.

- The users feel a lot of stress from necessity of evaluating all the solutions.
- The number of evaluation by the users tends to be large only even to get feasible solutions.
- Simultaneous evaluation of many solutions by the user is a very difficult task because they are animated pictures.

Many of previous studies on IGA treated to generate static image. In applications that solutions are temporal patterns such as animation, some devices for presenting solutions are needed [8].

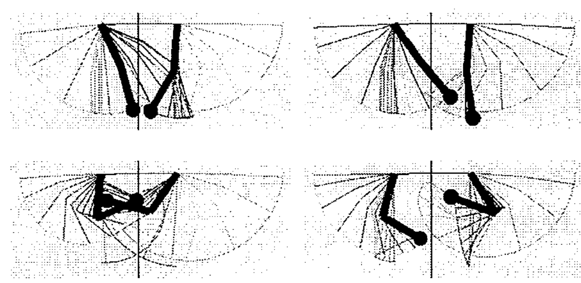

Fig. 4: Examples of presented solutions in Interactive GA.

Concluding the preliminary study, the characteristics of the studied methods are summarized as follows:

- Multi-objective GA
  - After searching of the Pareto optimal solutions with computer, user selects the preferred solutions from the obtained alternatives.
  - The constraints are satisfied in search process by computer.
  - Preference of the users is not reflected in search process.
  - Many similar solutions are presented to the users.
- IGA
  - The users evaluate the solutions in the searching process.
  - Preference of the users is reflected in the search process.
  - Infeasible solutions are presented to the users.

3. Proposed Method

3.1. Concept of the Method

To construct a computer supported method for the target problem, the followings must be taken into account. First, feasible solutions that satisfy the constraints must be found as solutions of multi-objective optimization by computer. Second, preference of the users must be reflected in searching process as IGA. In this section, we discuss the design concept of the method that satisfies the above two items.

It is assumed that each of the criteria described in Section 2 have many local optimal solutions. We consider that the Pareto optimal set is structured by assembly of separated subset in the decision variable space. We call such the subset as the local Pareto solution set. Figure 5 illustrates local Pareto optimal sets in evaluation space and in decision variable space. Symbols P1 ~P4 in Fig. 5 show the local Pareto optimal sets.

We assume that the preferred solution of the users is included in Pareto optimal set, and that the region including preferred solution is bounded. The region, however, cannot be known in advance. We expect that region to be searched is limited in neighborhood of a final solution, when computer search selectively the neighborhood of more preferred solutions in search process.

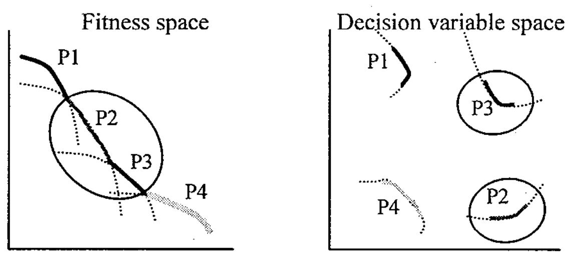

Fig. 5: The local Pareto solution sets.

Even when preferred solutions located closely each other in the fitness space, there exists some possibility that they are located separately in the decision variable space. Ellipses in Fig. 5 show such situation.

According to the above discussion, we expect that the search will advance efficiently if the method searches separated local Pareto solutions in parallel and search the neighborhood of preferred solutions by the users. It is adopted as design concept of proposal method.

This concept requires the following techniques for realization.

- Parallel search of local Pareto optimal sets.
- Selection of representations from the Pareto optimal set.
- Presentation of the alternatives animation images with less stress on the users and acquirement the information of the preference.

3.2. Elementary Techniques

3.2.1. Parallel search of local Pareto optimal set using genotypic clustering

A method called as genotypic clustering is used in order to search the local Pareto optimal sets in parallel and to select alternatives from Pareto optimal set.

The genotypic clustering is a method to obtain the local optimal solutions of multi-modal function by using GA simultaneous [5]. The method divides the population so that individuals having similar gene may be included in the same population. Since divided population is processed by the selection procedure independently, it is expected that each population converges independently into various local optimal solutions.

In multi-objective optimization, it is expected that the genotypic clustering can find various the local Pareto optimal sets in a similar manner. It is also expected that distribution of individual is averaged because the divided populations have similar individuals.

For clustering, Classit that clustering the real number vectors into n-tree is used [6]. POSS was used as fundamental generation alternation model [4] .

3.2.2. Presentation and Evaluation of Animation Images

So as to reduce stress on the users in measuring the preference of them, a technique named the sort using pair-wise comparison was adopted for presentation of the alternatives animated images.

The sort using pair-wise comparison is the technique that sorts the alternative into the order of preference of the users by repeating pair-wise comparison of the images systematically. We assume that the users can compare any alternatives, and the results of comparison do not include contradiction.

Two animations are played in a window of the display in parallel. The users are required to answer which is preferred by pushing button on the bottom of the window.

3.3. Algorithm

We construct an algorithm combining the methods described in Section 3.2. Figure 6 and the following sketch the algorithm of the proposed method.

(1) Generate individuals randomly as initial population.
(2) Divide the population into subpopulations using Classit.
(3) Run the Pareto optimal selection strategy on each subpopulation.
(4) If the number of individuals in the population is less than *MaxIndi*, go to (6).
(5) Divide the population into *AimIndi* using Classit, then pick up one individual randomly from each divided cluster, and remove the rest.
(6) If generation alternation is repeated G times then go to (7), otherwise go back (3).
(7) Merge all the subpopulations into one, and let the number of individual of merged population be N.
(8) Delete the dominated individuals in the population, and then thin out the left individuals till it will be *UserIndi* individuals.
(9) User repeats pairwise comparison of individuals. Computer sorts the individuals using the answer of the user.
(10) Generate the children by crossover. Parent individuals for crossover are selected from the sorted individuals according to probability proportional to the order of preference.
(11) Go back to (10) until the number of individual gets N.
(12) Stop if terminal condition is satisfied , otherwise go back to (2).

The real number vector and UNDX was used as coding and crossover respectively.

4. Evaluation of Proposed Method

We applied the proposed method to the problem of Model 2. The quality of solutions obtained by the method and the stress given to the users was examined. Simple IGA and interactive simplex method were also applied for comparison.

4.1. Experiments and Results

Same number of pair-wise comparison was allowed in all the three methods. The pairwise comparison evaluation with 7 levels was used to measure the quality of solution. The questionnaire answered on 7 level scale about 10 questions was used to measure stress given to the users.

The following parameters were used in all the methods: The divide number of spline is 3. The terminal condition is when the number of the pairwise comparison exceeds 100, the number of Pareto optimal selection strategy crossover is 10, *MaxIndi* is 50, *AimIndi* is 40, *UserIndi* is 10, G is 15 and the number of initial individuals is 200. In simple IGA, used parameters as follows: the number of crossover is 15, *UserIndi* is 15 and the number of initial individuals is 15. In interactive simplex method on genotypic space, the number of initial individuals is 15. Figure 9 shows example of generated solutions.

In the experiment of designing fully by hand, many users obtained a final solution modifying from the initial solution a little.

In the proposed method, some criteria including constraints of the alternatives were optimized to some degree by computer. For that reason many work required to the users were to judge subjective evaluation, such as point for passing the object and poses of both arms.

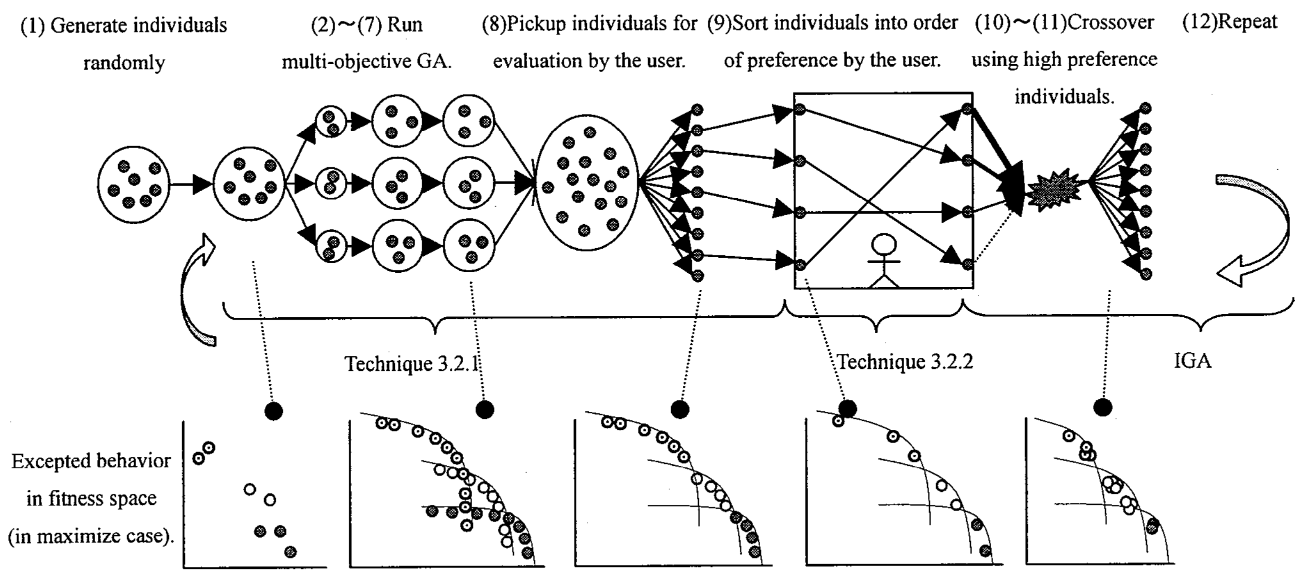

Fig. 6: Algorithm of proposed method

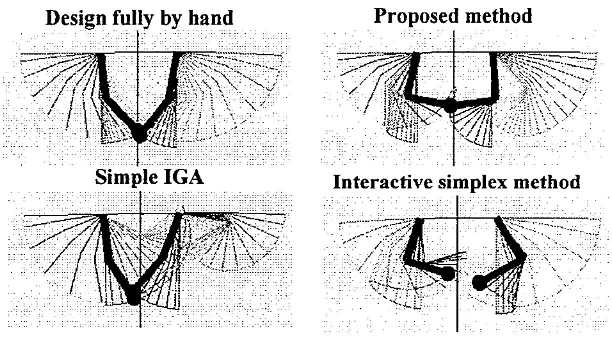

Fig. 9: Examples of generated images

In the simple IGA and the interactive simplex method, the alternatives which do not satisfy the constraints were presented to the users, and many works required to the users were to just find feasible solutions.

4.2. Analysis of results

We applied variance analysis to the data obtained by the pairwise comparison on the quality of the solutions obtained [7].

Figure 7 shows 5% and 1% confidence interval of evaluation. It shows that the proposed method can generate higher quality solution than the other two conversional methods. However, it also shows that there is not significant difference in quality of solutions between the proposed method and design fully by hand.

We also applied the principal component analysis to the result of questionnaire survey about difference in impression on each method. We name the highest rank factor 'tiredness'. Figure 8 shows confidence interval about tiredness. It shows that proposed method gives less stress on the users than the other methods.

5. Conclusions

In this paper, we proposed the interactive genetic algorithms enhanced by limiting the searching region efficiently considering explicit criteria that are evaluated easily by computer. The proposed method is applied to a problem of generating path of link mechanism for making human like motions as animation by computer graphics. Experiments using several subjects were carried out, and it is shown that the proposed method generated higher quality solutions with less stress on the users than the conventional methods.

The following are subjects of future study: Improvement of

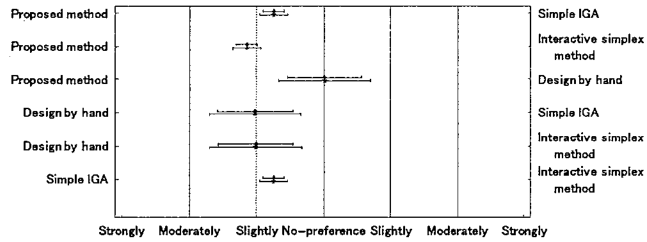

Fig. 7: Confidence interval of quality of generated animations using the methods

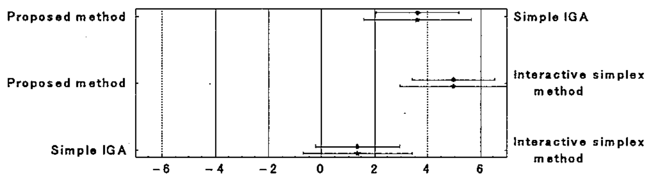

Fig. 8: Confidence interval of tiredness using the methods

the reaction time by reducing time for search in order to apply the proposed method to 3-dimensional complicated models such as Model 1. Revision of the alternatives by the users in order to search just as they intended. Adjustment of the balance of searching and improvement by the users.

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