Analysis of Direct Manipulation in Interactive Evolutionary Computation on Fitness Landscape

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Abstract - Interactive evolutionary computation (IEC), which takes user's evaluation as fitness function, has low performance for local search due to the limitation of population size and generation length. To solve that, direct manipulation (DM) method, well known in HCI field, of evolution for IEC has been proposed. It allows the user to manipulate individuals directly, instead of using evolutionary operators as an interface to each individual. In this paper, we analyze the usefulness of DM with fitness landscape and N-K model. We have applied the DM concept to the fashion design system based on IEC, and analyzed the results with the concept of fitness landscape and Boolean hypercube.

I. INTRODUCTION

Interactive evolutionary computation (IEC) is a method using user's evaluation of each individual as fitness value instead of fitness function of EC. Through this approach, EC can be applied to the artistic domains such as music or design which has difficulty in deriving formal fitness functions [1].

In the meantime, to guarantee the performance of EC, it is desirable to maintain the population of evolution as large as possible. It is also required to afford many generations enough to let the population converge. Unfortunately, these requirements cannot be satisfied in IEC applications because it relies on user's evaluation for every individual. Human operators cannot evaluate large number of individuals nor hundreds of generations, which limits the population size and generation length.

We have already proposed the direct manipulation (DM) of evolution as a solution of the limitation [2]. As shown in several experiments, it efficiently remedies the shortcoming of IEC that lacks of the capability of local search while having a merit in global search.

In this paper, we analyze the usefulness of DM with some fitness landscapes. We have applied the DM concept to the fashion design system based on IEC, conducted several experiments and analyzed the results with the concept of fitness landscape and Boolean hypercube. Section II introduces fitness function and N-K model as background. Section III describes the fashion design system using IGA we have proposed, the concept of DM and its interface to IGA application. Section IV provides some experimental results and analysis.

II. FITNESS LANDSCAPE AND N-K MODEL

Typically, a fitness landscape describes a surface of fitness values over some sort of representational space that may be searched by evolutionary operators acting on a population of individual points sampled from that space [3]. It has been proven to be very powerful in evolutionary theory, shown to be useful for understanding the behavior of combinatorial optimization algorithms, and can help in predicting their performance. Viewing the search space, the set of all (candidates) solutions, as a landscape, a heuristic algorithm can be thought of as navigating through it in order to find the highest peak of that; the height reflects the fitness of the solution associated with that point [4].

More formally, a fitness landscape (S, f, d) of a problem instance for a given some optimization problem consists of a set of points (solutions) S, a fitness function $f: S \rightarrow R$, which assigns a real-valued fitness to each of the points in S, and a distance measure d, which defines the spatial structure of the landscape. The fitness landscape can thus be interpreted as a graph $G_L = (V, E)$ with vertex set $V = S$ and edge set $E = \{(s, s') \in S \times S \mid d(s, s') = d_{\min}\}$, with $d_{\min}$ denoting the minimum distance between two points in the search space. The diameter $diam\ G_L$ is defined as the maximum distance between the points in the search space. For binary-coded problems $(S = \{0,1\}^n)$, the graph G_L is a hypercube of dimension n, and the distance measure is the Hamming distance between bit strings. The minimum distance $d_{\min}$ is 1 (one bit with a different value), and the maximum distance is $diam\ G_L = n$.

Boolean hypercube is a kind of optional fitness landscape, which consists of combinatorial objects and one-mutant neighbors. All of the options on that are defined as combinatorial objects because they show the symbolic relationships between discrete mathematical elements belonging to a finite set. The concept of a one-mutant neighbor is used to evaluate whether changing between two associated options on the landscape would make the end result "fitter." Fig. 1 shows the 4 bits Boolean hypercube and the "adaptive walk" process to the local optima with random assigned fitness value.

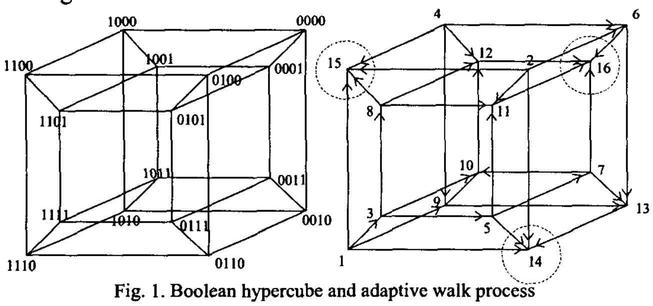
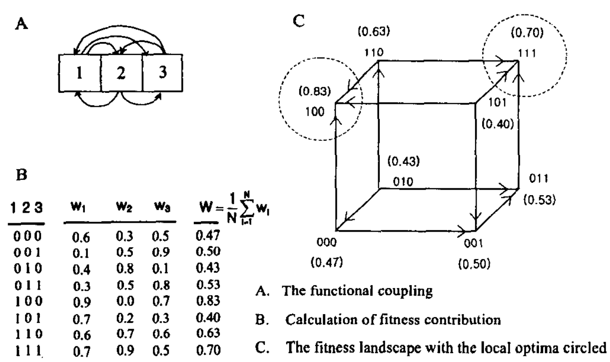


Fig. 1. Boolean hypercube and adaptive walk process

Kauffman introduced a class of stochastically-defined fitness landscapes over bit strings (binary-coded) called the N-K landscape model [5]. Here, N refers to the number of parts of system (number of bits, genes in a genotype) and K is a linkage among the parts that reflects the epistatic interactions. Parameter K can be tuned to adjust the "ruggedness" of the landscapes. When K=0, the landscapes are linear, and when K=N-1 the landscapes are random. Fig. 2 shows simple N-K model with N=3, K=2.



1 2 3	w_1	w_2	w_3	$W=\frac{1}{N}\sum_{i=1}^{N} w_i$
0 0 0	0.6	0.3	0.5	0.47
0 0 1	0.1	0.5	0.9	0.50
0 1 0	0.4	0.8	0.1	0.43
0 1 1	0.3	0.5	0.8	0.53
1 0 0	0.9	0.0	0.7	0.83
1 0 1	0.7	0.2	0.3	0.40
1 1 0	0.6	0.7	0.6	0.63
1 1 1	0.7	0.9	0.5	0.70

A. The functional coupling

B. Calculation of fitness contribution

C. The fitness landscape with the local optima circled

Fig. 2. N-K fitness landscape example with N=3, K=2

III. DIRECT MANIPULATION FOR EVOLUTION

A. Fashion Design System Using IGA

We have developed fashion design aid system using interactive GA, to solve the problems of conventional systems such as Creative Designer System from Gerber [6] and Virtual Reality [7]. Their problem was too hard to use for non-professionals. Some other systems developed by Nakanishi using interactive EC [8] solved that problem, but most of its productions were somewhat impractical due to the lack of realistic knowledge on the domain of fashion. Our system provided a solution to encode domain specific knowledge into the system [9]. Fig. 3 shows the overall system configuration.

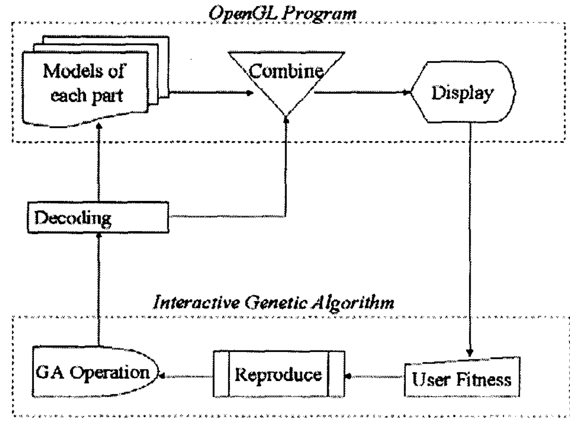


Fig. 3. System overview

The system uses IGA to get a preferable design by user. There is a database of partial design elements. Each design is stored in 3D model as an OpenGL [10, 11] list converted from 3D Studio MAX modeling file. System selects the model of each part according to the decoded information from individual chromosome, and combines them into a number of individual designs. There are 34 parts of neck and body, 12 parts of arm and sleeve and 9 parts of skirt and waistline. Each of them can take their own color out of 8. Therefore the size of search space amount to 1,880,064 resulted from $34\times8\times12\times8\times9\times8$. Fig. 4 shows how the system decodes the bit string to 3D model.

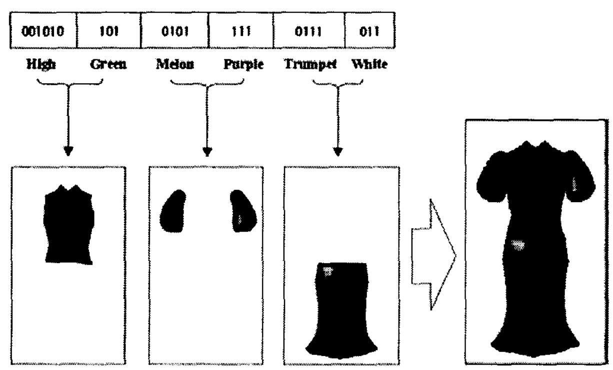


Fig. 4. 3D model gene encoding

The system searches the best design out of 1,880,064 candidates according to the user's feedback on preference and emotion. After a user does some evaluation to each individual, system reproduces the population proportional to the fitness value of each design, and applies crossover and mutation operators to make the next population. Iteration of these processes can produce the population having higher fitness value, namely better designs. Through this, user's emotions are reflected to the evolution. As the result, selected characteristics influenced by user's emotion will appear at the next population with large possibility. Therefore, the population evolves based on user's emotion. Fig. 5 shows the interface of fashion design system.

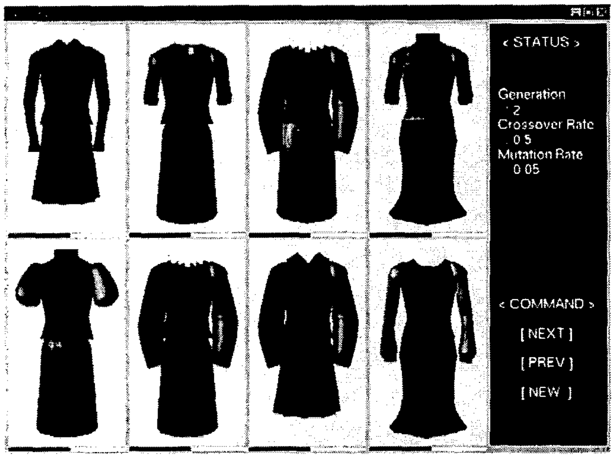


Fig. 5. Program interface

B. Experimental Results

We have conducted several experiments with this system and Fig. 6 and 7 are some results of them. Fig. 6 shows the results of convergence test of cool-looking design and Fig. 7 shows results of subjective test of cool-looking and splendid-looking design.

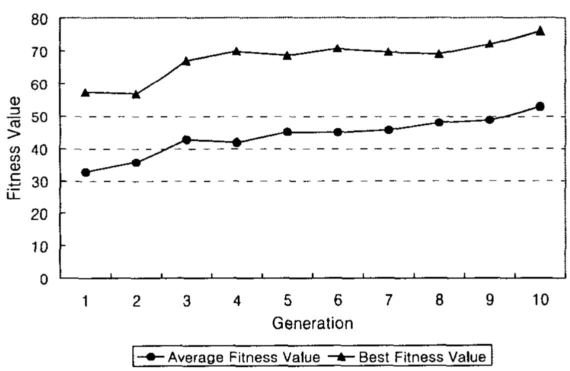


Fig. 6. Convergence test results of cool-looking design

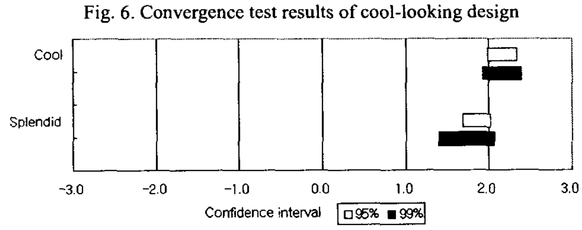


Fig. 7. Subjective test results of cool-looking and splendid looking

C. Direct Manipulation for IGA

Direct manipulation is a style of human machine interaction design which features a natural representation of task objects and actions promoting the notion of people performing a task themselves (directly) not through an intermediary [12]. The DM is being studied extensively and many applications are being developed.

EC algorithm is advantageous in global search caused by using probabilistic operators on a population. However, that fact can be a defect in local search such as deriving an exact solution from near-solution. It becomes worse in IEC application, which possesses limitation on its population size and generation length. To solve that, we have proposed modified DM concept and implemented a DM interface to the IGA fashion design aid system. As shown in several experiments, this approach leaves the local search to the user's direct manipulation while evolutionary operators perform the global search. So we could get efficient retrieval performance within a short generation length of IEC application.

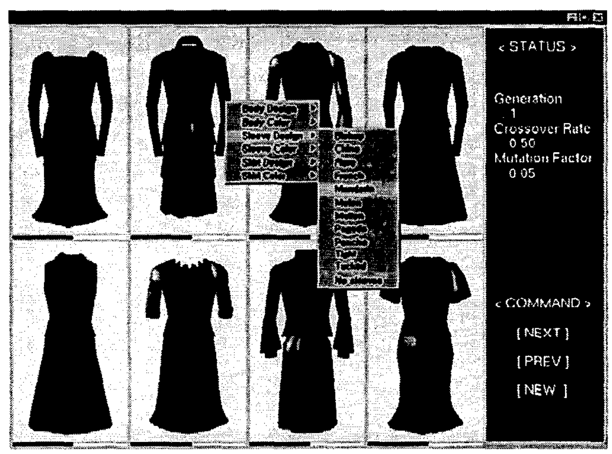


Fig. 8. Direct manipulation interface

We have implemented the DM with a pop-up style interface to meet our several requirements (Fig. 8). User can manipulate the individuals without knowing the foundation of genotype because the interface shows the characteristics of the design such as detail name or color of it, not the genotype itself. Fig. 9 shows the chart of design parts and colors that user can change using DM interface. If a user wants to change the body design from the 'double' to the 'off', he just selects the off design in the pop-up menu though he does not know what the genotype of the 'double' or the 'off' is. Then, the system changes that automatically from '000100' appropriate to the double design to '001101' appropriate to the off design.

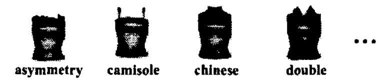
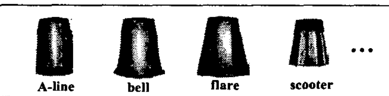
Body design	
Sleeve design	
Skirt Design	
Body color Sleeve color Skirt color	white, black, yellow, azure, purple, ···

Fig. 9. Changeable design parts and colors through DM interface

IV. EXPERIMENTAL RESULTS

To show the usefulness of DM interface, two experiments have been conducted. We check the possibility of generation reduction by DM and investigate user's satisfaction while using DM. Every experiment has been operated under the same condition of 0.5 crossover rate, 0.05 mutation rate and elitist preserving strategy and 10 graduated students are participated. We limit the total generation as 20 for the first experiment, and 10 for the second experiment. The population is composed of 8 individuals.

At first, we have asked subjects continue retrieval until their preferable design of cool-looking comes out using IGA system having no DM interface and examined intermediate designs during the test to find those have just one different point (design part or color) to the user's final selected design. Finally, we count the generation steps to be able to shorten if they use DM.

For the second experiment, we have informed the subjects of the existence and the function of DM interface, including that they can apply the undoing if they are not satisfied with the result of DM. After that we have asked them to find their own cool-looking design using the system and the DM interface. During the search we have recorded the frequency of activation and cancellation of DM to validate user's manipulation.

Table 1 shows a minimum, maximum and average generation lengths to be able to shorten by DM according to the 7 results of the first experiment.

TABLE 1. GENERATIONS SHORTENED BY DIRECT MANIPULATION

Minimum	Maximum	Average
3	9	6.57

Fig. 10 is one result of the first experiment that shows a transition of schemata in approximated solution, and Fig. 11 shows captured pictures of the 5th and the 10th generations. The 10th generation has the approximated solution of subject, and we can see the fact that there are some possibilities of generation reduction from the 5th to the 10th if the subject uses DM.

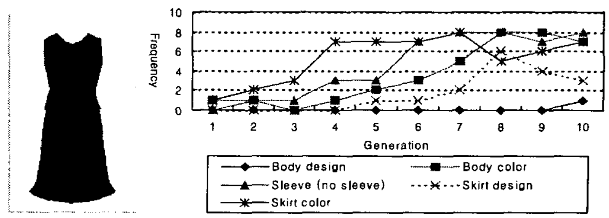


Fig. 10. An example of transitions of schemata in approximated solution for each generation

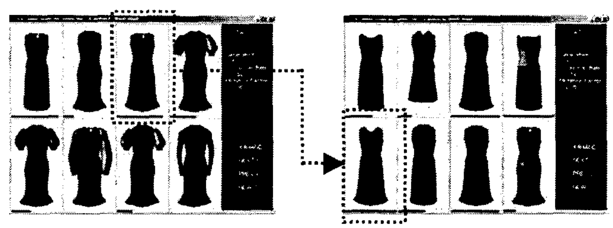


Fig. 11. Captured pictures at the 5th and 10th generation for the same example of Fig. 10

TABLE 2. PERCENTAGE OF VALID MANIPULATION

Maximum number of available manipulation	Average number of direct manipulation	Average number of cancellation	Percentage of cancellation	Percentage of valid manipulation
10 times	9.3 times	0.9 times	9.68%	84.0%

Table 2 shows the results of second experiment, which has been conducted for the validation of DM.

Fig. 12 shows one example of DM performed by one subject in the 9th generation of the second experiment, and it explains how the DM helps the evolution in local search. Users derive a better individual from near-solution by DM. In that example, the sleeve design of the individual is 'Mandarin' before manipulation is marked as 4 bits '0100' on genotype. The user replaced it with a new design 'No sleeve' resulting in bits change to '1011,' which gives the user more cool feeling. If he had to get it with normal GA operators such as crossover and mutation, he must have searched for a long generation to be selected by the probability as we have shown in the first experiment.

To prove this more theoretically, we consider the fitness landscape of that example using binary hypercube. As stated in Section II, binary-coded problem can be visualized as a hypercube with n bit dimension, Hamming distance between bit strings and fitness assigned every vertex. However, it is the problem that IEC system has no explicit fitness function. People cannot evaluate all the possible construction of design parts and colors, i.e., it is almost impossible to mark the fitness of all possible designs. We can solve this problem through fixing all other parts and colors except the only changing part of that example, arm and sleeve design, so that the problem becomes to small local optimum search.

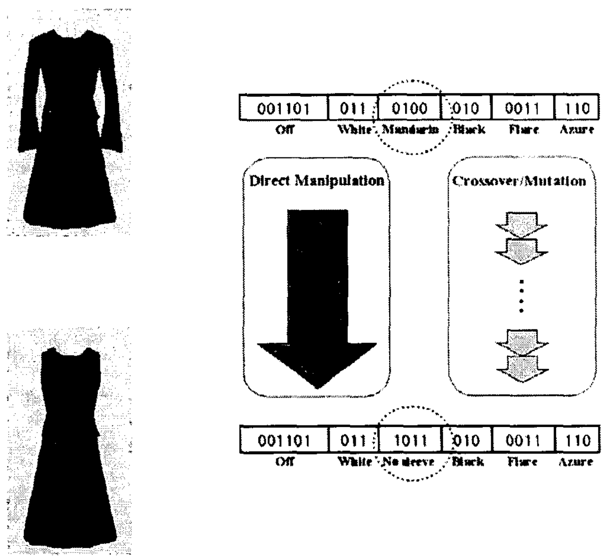


Fig. 12. An example of DM of evolution with respect to corresponding genotype

Therefore for analyzing this example, we have changed problem to the simple one. Our system has 12 number of arm and sleeve designs encoded in 4 bits. Fig. 13 is the encoding of arm and sleeve designs chart. If user only selects one design from them, it may not be difficult problem. We asked the subject to mark the fitness of several fashion designs that differ only the shapes of the sleeve and arm designs and he was able to give the fitness of designs. The fixed design parts and colors for the evaluation are as follows. The body design is "Off" and the color is "White," the skirt design is "Flare" and the color is "Azure" and the sleeve color is "black." We could draw some 4 bits hypercube using user's evaluation, to demonstrate the movement of the genetic operators and DM interface. Every vertex of hypercube has each composed design and fitness value, and every edge expresses the one-mutant neighbor relation. The start point of arm and sleeve design is "Mandarin" and the destination is "No Sleeve." Fig. 14 shows the relative fitness values, i.e., user's evaluation values, where the extent is from 0 to 100 with interval 5. The optimum is "No Sleeve" and sub-optimum is "China".

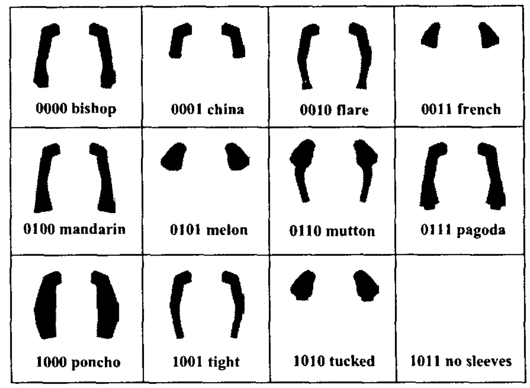


Fig. 13. Arm and sleeve design encoded in 4 bits

Fig. 15 and 16 are the binary hypercube that consists of one-mutant neighbors having fitness from user's evaluation. Fig. 15 shows the possible movements from "Mandarin" to "No Sleeve" using mutation operators. The Hamming distance is 4, i.e., the shortest path is at least 4 to go to the destination. So, if we use only mutation operator, then at least there must be 4 times of mutation. The dotted red circle shows the sub-optimum that has no one-mutant neighbor having lower fitness than it. Sometimes it may be difficult to arrive to the local optimum from that. Fig. 16 shows DM method can reduce the steps going to local optimum easily with high probability than crossover or mutation, i.e., user can find optimal design from approximated designs faster through DM interface than normal genetic operators. Therefore, using DM to change some design parts of fashion or colors can be efficient in local search in the fashion design system.

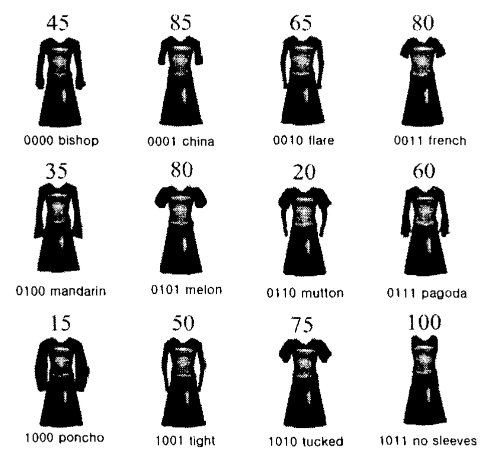


Fig. 14. The relative fitness evaluated by one subject

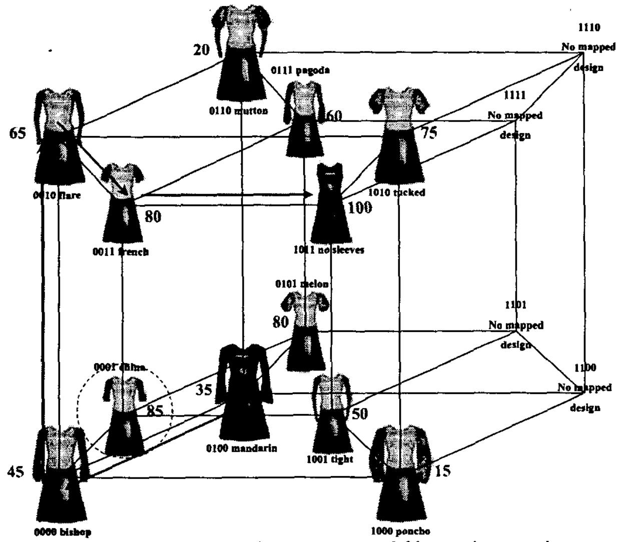


Fig. 15. Possible path through the one-mutant neighbors using genetic operator

From the results and analysis we can reach several conclusions. First, we can save time and effort to retrieve if we use DM to reduce generation length. The experimental results support that assertion and the hypercube has been shown it well. Second, we can say that the subjects were significantly satisfied with the result of DM, from the fact that they have hardly canceled their DM and the fact that they were still using the DM interface in the last generation at second experiment.

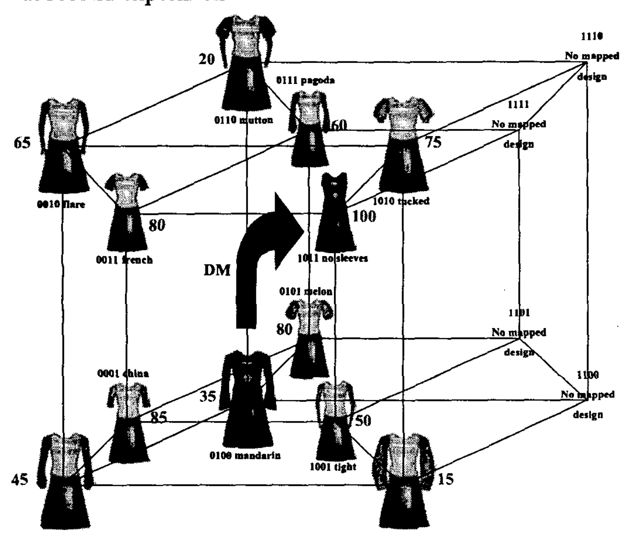


Fig. 16. The shortest way while using DM method

V. CONCLUDING REMARKS

We have conducted experiments and analyzed proposed DM of evolution for an IGA application. Originally DM means a direct control of objects without visible interface in the field of HCI, but we have modified this concept and provided a prototype interface of that, which allows users to manipulate the genotype directly instead of relying on the probabilistic GA operators. As shown in the analysis, the proposed DM interface improves the local search performance of IGA, leaving the global search to the original GA operators. With an analysis of the results we could assert that it was promising.

There remain several points to improve our method. First of all, we need more general solution about the proof of the effectiveness of DM. Also, the balance of IGA search and DM must be studied more extensively. It is important to keep a balance of IGA search and DM, avoiding the reduction of global search performance of GA. Finally, we have to prove that the proposed DM approach is desirable for an IEC application by applying it to other IEC systems. There are many IEC applications such as music or drawing, and we need to check the possibility of using DM concept to those applications of other fields.

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