# Short Paper

## Intelligent Decision Making Based on GA for Creative Apparel Styling*

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This paper describes a conceptual intelligent design system, which chiefly consists of a searching mechanism and a classifier. The searching mechanism is based on genetic algorithm (GA) to search for various evolved types of clothing combinations, and the classifier is constructed through learning and knowledge acquisition by an artificial neural network (ANN) to play a roll of evaluation mechanism to classify the evolved clothing wearing style combinations. With the assistance of this system, a user without any expertise of fashion design can effectively find out the design schema, which is the best-fitted solution for the demand.

***Keywords:*** conceptual design, knowledge acquisition, wearing style, search mechanism, genetic algorithm

## 1. INTRODUCTION

Recently, application of computer technology in the textile field is widely spreading. The computer has enhanced a lot not only the functions of the hardware but the applications of software. However, most of its applications in textile industry focus on manufacturing processes and quality improvement [1]. Some of them are applied to the computer aided design (CAD) systems [2-6]. H. Rödel *et al*. [2] emphasized the necessity of development of powerful 3D CAD systems for the textile and clothing industry in the paper. The research reported in [3] proposed a 3D-CAD system consisting of a measurement system for the wearer's body shape and a garment simulation system to perform the simulation of Japanese yukata. The basic techniques for realization of the deformable body model were investigated in [4]. Moreover, a new 3D garment simulation result update algorithm for the 2D garment pattern design modification was presented in [5]. With this approach, the 3D garment fitting simulation does not need to repeat the entire simulation for every modification and can react to the 2D pattern modification efficiently and speedily. In order to mass-customize clothes, it is essential to consider individual body shape using computerized 3D body models. The development of an interactive body model that can be altered with individual body shape for the purpose of computerized pattern making was described in [6].

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The developed CAD system mentioned above is indeed added more and more helpful functions by means of the enhanced power of computer to enable the user to proceed apparel design more quickly and accurately. However, the perceptions and inspirations for apparel styling design still deeply depend on the experiences and expertise of professional designers and cannot be supported by the CAD system. Apparel styling design is a broad-based art to combine types, colors, materials, and the fashion design elements, related to variables of perceptions and inspirations. Despite the enhancing power of computer, it still cannot be helpful for all the design procedure of clothing design. To create a prefect apparel styling design still deeply depends on a professional designer, who is of expertise and experience, to provide his/her perceptions and inspirations. A CAD system for apparel design still cannot produce design inspiration for a designer so far. The lack of perceptions and inspirations for most of CAD systems applied in the clothing design needs improving a lot.

As a nonlinear relationship of "1 to *n*" between "Value" and "Object" for product designing [7, 8], the designing of wearing styles proposed in this study is deemed to be a nonlinear problem. Because there are limitless combinations of various garments appropriate for a given occasion, a search method is necessary to be adopted to help find the best-fit solution to the demanded wearing style. In this paper, a genetic algorithm (GA) [9], a population-to-population approach to work from a rich database of points simultaneously (a population of strings) combing many peaks in parallel to keep the search from local optima, is used. In this study, we propose an intelligent decision making system for apparel styling design based on a GA and neural network to search for appropriate apparel styling for consumers' demand. Nowadays, it is more and more important for people to dress properly for different occasions to show their politeness. There are in fact already many studies confirm that higher order needs, such as belonging and self-esteem, can be satisfied through clothing [10]. Some people might even regard clothing as a tool for validation of the self or illustration in social interaction through which the self can be established. Without professional suggestions from an experienced designer, customers can hardly show appropriate wearing styles on their own. Generally, there are four kinds of wearing style classified as "Modern", "Elegant", "Casual", and "Sporty" [11, 12]. The sense of wearing style can be reflected through different combinations of various types of garments. It is limitless, and there is no longer one type of garment for a given occasion. Therefore, to help the consumer by showing him/her the various combinations possible for various occasions with different wearing styles becomes more and more important for a salesperson in the apparel industry.

To solve these problems, in this paper we extract wearing style information from the experts, using ANN to acquire their knowledge through learning various wearing style instances designed by the professional designer. Thus, a professional wearing styling classifier can be constructed. To obtain various combinations of garment types, A GA search method based on the mechanism of genetic inheritance is adopted in this paper. The evolved combinations of garment type by the GA search mechanism can be evaluated how close to each other between the specific sense of wearing style desired by the customer and itself. After generations, the one closest to the customer's demand can thus be acquired. Through the developed system with intelligence, a user or an apparel salesperson can effectively determine what types of garments should be put together into a combination to show the sense of wearing style demanded by the customer.

## 2. FRAMEWORK OF INTELLIGENT DECISION MAKING SYSTEM

As shown in Fig. 1, the system consists of four major components, such as search mechanism, evaluation mechanism, and knowledge database, and user interface, each of these is described briefly as follows.

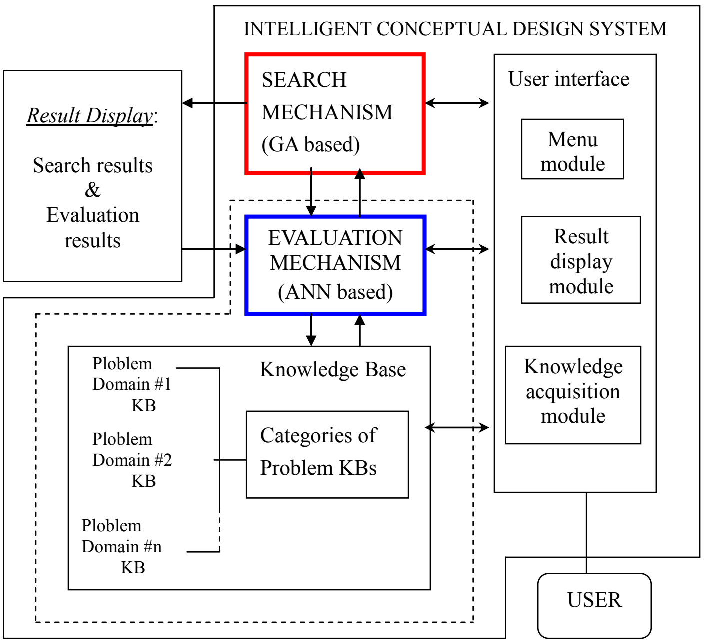



Fig. 1. Overall structure of the intelligent conceptual design system.

(1) Search Mechanism

The search mechanism is based on genetic algorithm (GA), which is an optimization technique inspired by biological evolution [9]. Based on the natural evolution concept, the GA is computationally simple and powerful in its search for improvement and is able to rapidly converge by continuously identifying solutions that are globally optimal with a large search space. By using the random selection mechanism, the GA has been proven to be theoretically robust and empirically applicable for searching in complex space.

(2) Evaluation Mechanism, Knowledge Base, and User Interface

The knowledge database consists of two parts, one is the database of already trained connection weights, and the other is the database of training sets and testing sets. The user interface allows the user to modify and upgrade the knowledge database to create bases for new problem domains to be included in the evaluation mechanism to keep them facile. Through the interaction between the search mechanism and evaluation mechanism, several fit solution (*i.e.*, chromosome), which are evaluated by evaluation mechanism using ANN to be of fitness approaching to 1, can thus be obtained from evolutions by search mechanism.

## 3. ESTABLISHMENT OF SEARCH MECHANISM

To solve a problem, the GA randomly generates a set of solutions for the first generation. Each solution is called a chromosome that is usually in the form of a binary string. According to a fitness function, a fitness value is assigned to each solution. The fitness values of these initial solutions may be poor, however, they will rise as better solutions survive in the next generation. A new generation is produced through the following three basic operations [9].

(1) Randomly generate an initial solution set (population) of $N$ strings and evaluate each solution by fitness function.
(2) If the termination condition does not meet, do
Repeat {Select parents for crossover.
Generate offspring.
Mutate some of the numbers.
Merge mutants and offspring into population.
Cull some members of the population.}
(3) Stop and return the best fitted solution.

### 3.1 Encoding

In order to apply GAs to our problem, we firstly need to encode the parameters of the factors as a binary string. Two important factors need determining, *i.e.*, the "type" and "color". The former denotes the garment "type" used in the clothing combination for wearing style. The latter denotes the garment "color" used in the clothing combination for wearing style. There are five basic categories including coat, shirt, vest, skirt, and trousers, which are five different "type" factors in this paper. Each of them is equipped with various attributes. For instance, there are four options during wearing for the "coat" attribute of "type" factor, *i.e.*, (a) none (b) coat (c) odd jacket (d) sport jumper, which can be illustrated as Fig. 2. Thus, there are two bits needed for encoding the "coat" type. In other words, the encoding ways such as (a) 00 (b) 01 (c) 10 (d) 11, which are the obtained solutions from the search mechanism and represent "nothing" dressed, dressed in "coat", dressed in "odd jacket", and dressed in "sport jumper" respectively.

The adopted color tones for the garment "type" factor mentioned above are concluded as the "color" factor. The CMYK color model [13], which is defined with primary

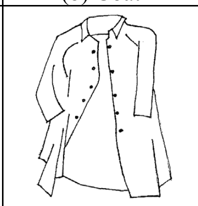
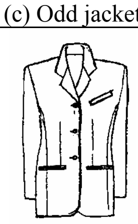
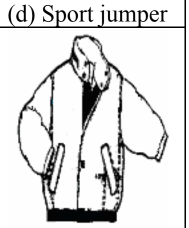
| (a) None | (b) Coat | (c) Odd jacket | (d) Sport jumper |
|---|---|---|---|
| |  |  |  |
| (a) 00 | (b) 01 | (c) 10 | (d) 11 |

Fig. 2. Illustrations of attribute "coat".

**Table 1. Match factors and attributes for apparel styling.**

| Match Parameters | | | Attributes | | the Encoded | the Decoded | Gene size (bits) | Bit orders in chromosome |
|---|---|---|---|---|---|---|---|---|
| Type | coat | $F_1$ | none<br>Coat<br>Odd jacket<br>Sport jumper | | 00<br>01<br>10<br>11 | 0.0000<br>0.3333<br>0.6667<br>1.0000 | 2 | 1~2 |
| | shirt | $F_2$ | none<br>Shirt<br>T-shirt<br>High-necked blouse | | 00<br>01<br>10<br>11 | 0.0000<br>0.3333<br>0.6667<br>1.0000 | 2 | 3~4 |
| | vest | $F_3$ | none<br>on | | 0<br>1 | 0.0000<br>1.0000 | 1 | 5 |
| | skirt | $F_4$ | none<br>Pant skirt<br>Tight skirt<br>Pleats skirt | | 00<br>01<br>10<br>11 | 0.0000<br>0.3333<br>0.6667<br>1.0000 | 2 | 6~7 |
| | trousers | $F_5$ | none<br>AB trousers<br>Long-kneed trousers<br>Half trousers | | 00<br>01<br>10<br>11 | 0.0000<br>0.3333<br>0.6667<br>1.0000 | 2 | 8~9 |
| Color tones | coat | $F_{11}$ | C | 0~15 level | 0000~1111 | 0~1 | 4 | 10~13 |
| | | $f_{12}$ | M | 0~15 level | 0000~1111 | 0~1 | 4 | 14~17 |
| | | $f_{13}$ | Y | 0~15 level | 0000~1111 | 0~1 | 4 | 18~21 |
| | | $f_{14}$ | K | 0~15 level | 0000~1111 | 0~1 | 4 | 22~25 |
| | shirt | $f_{21}$ | C | 0~15 level | 0000~1111 | 0~1 | 4 | 26~29 |
| | | $f_{22}$ | M | 0~15 level | 0000~1111 | 0~1 | 4 | 30~33 |
| | | $f_{23}$ | Y | 0~15 level | 0000~1111 | 0~1 | 4 | 34~37 |
| | | $f_{24}$ | K | 0~15 level | 0000~1111 | 0~1 | 4 | 38~41 |
| | vest | $f_{31}$ | C | 0~15 level | 0000~1111 | 0~1 | 4 | 42~45 |
| | | $f_{32}$ | M | 0~15 level | 0000~1111 | 0~1 | 4 | 46~49 |
| | | $f_{33}$ | Y | 0~15 level | 0000~1111 | 0~1 | 4 | 50~53 |
| | | $f_{34}$ | K | 0~15 level | 0000~1111 | 0~1 | 4 | 54~57 |
| | skirt | $f_{41}$ | C | 0~15 level | 0000~1111 | 0~1 | 4 | 58~61 |
| | | $f_{42}$ | M | 0~15 level | 0000~1111 | 0~1 | 4 | 62~65 |
| | | $f_{43}$ | Y | 0~15 level | 0000~1111 | 0~1 | 4 | 66~69 |
| | | $f_{44}$ | K | 0~15 level | 0000~1111 | 0~1 | 4 | 70~73 |
| | trousers | $f_{51}$ | C | 0~15 level | 0000~1111 | 0~1 | 4 | 74~77 |
| | | $f_{52}$ | M | 0~15 level | 0000~1111 | 0~1 | 4 | 78~81 |
| | | $f_{53}$ | Y | 0~15 level | 0000~1111 | 0~1 | 4 | 82~85 |
| | | $f_{54}$ | K | 0~15 level | 0000~1111 | 0~1 | 4 | 86~89 |

Layout of chromosome

| 74~89 | 58~73 | 42~57 | 26~41 | 10~25 | 8,9 | 6,7 | 5 | 3,4 | 1,2 |
|---|---|---|---|---|---|---|---|---|---|
| $F_{51}$~$f_{54}$ | $f_{41}$~$f_{44}$ | $f_{31}$~$f_{34}$ | $f_{21}$~$f_{24}$ | $f_{11}$~$f_{14}$ | $F_5$ | $F_4$ | $F_3$ | $F_2$ | $F_1$ |

89 bits

Types: $F_1$: coat $F_2$: shirt $F_3$: vest $F_4$: skirt $F_5$: trousers

Coloring: $f_{11}$~$f_{14}$, $f_{21}$~$f_{24}$, $f_{31}$~$f_{34}$, $f_{41}$~$f_{44}$, $f_{51}$~$f_{54}$: denote four original colors (*i.e.*, C(4bits), M(4bits), Y(4bits), K(4bits)) for coat, shirt, vest, skirt, and trousers.

colors Cyan, Magenta, Yellow, and Black (*i.e.*, C, M, Y, and K) are applied in this study. Besides, there are 16 tone levels used for each of the original color above. Thus, each of the four original colors is encoded with 4 bits. There are totally 65,536 (= $2^4 \times 2^4 \times 2^4 \times 2^4$) kinds of color tones can be shown by the combinations of the four original color, *i.e.*, C, M, Y, K. Table 1 shows the two parameters and their attributes.

### 3.2 Chromosome

A main difference between genetic algorithms and more traditional optimization search algorithms is that genetic algorithms work with a coding of the parameter set and not the parameters themselves [9]. Thus, before any type of genetic search can be performed, a coding scheme must be determined to represent the parameters in the problem in hand. In this study, a binary coding is utilized and the bit-sizes of the encoding for the ten variables are as follows. Five of them are for the "pattern" such as "coat"($F_1$), "shirt" ($F_2$), "vest"($F_3$), "skirt"($F_4$), and "trousers"($F_5$), the bit-size of each of them is 2 bits for $F_1$, 2 bits for $F_2$, 1 bit for $F_3$, 2 bits for $F_4$, and 2 bits for $F_5$ respectively. The other five of them are for the "color" of each pattern, the bit-size for each single original color of C, M, Y, or K is all set as 4 bits. Thus a chromosome string consisting of 89 bits can be formed and its layout is shown in Table 1.

### 3.3 Fitness Function

There are four sets of apparel styling targets in this study, including Modern, Elegant, Casual, and Sporty. Each of them was encoded with 4-bit gene string, *i.e.*, 1000, 0100, 0010, and 0001 respectively. The 4-bit gene strings were utilized as the default output values for output nodes of ANN during learning. But it is possible for a consumer to desire a mixed fashion styling of the four above-mentioned styling. For instance, certain kind of apparel styling on much stronger modern fashion but not far away from elegant, a bit of leisure and a little of sporty feeling. In this circumstance the user can express the exact desired feeling in an alternative way by a quantification method instead of using linguistic way to describe the exact demand of apparel styling. Therefore, the user can indicate his desire by setting the weight vector, for instance, (0.8, 0.6, 0.2, 0.2) as the default desired styling target for the search mechanism to search for. In order to evaluate how close to the default target for each solution obtained by the evolution of search mechanism, each solution, consisting of 89 bits string, is decoded into 25 values ranging at [0, 1], and taken as the input values of input nodes for ANN to test. The ANN, which is of splendid fault tolerance capability, is applied to set up an evaluation mechanism to evaluate the fitness of each chromosome (*i.e.*, solution) obtained from evolutions of search mechanism shown as Fig. 1. Before the neural network is of evaluation capability in the application field, it has to go through training procedure so as to play an evaluator roll to give a fitness value for each chromosome by judging how close it approach to the target demanded. Comparing the tested output vector (*i.e.*, $Y_i'$) with default one (*i.e.*, the customer desired fashion target vector: $Y_i$), the less difference between them, the closer the fitness approach to 1, representing the searched chromosome is closely approaching to the default desired target fashion. The fitness of GA used in search mechanism can thus be set as Eq. (1).

$$Fitness(Y_i') = 1 - \sum_{i=1}^{4} |Y_i' - Y_i| / 4 \tag{1}$$

where

$Y_i$: default target value.
$Y_i'$: output value for each generation.

### 3.4 Necessary to Set Constrained Condition

There are some violations for the combination of apparel styling such as (a) simultaneously the trousers and skirts are dressed (b) simultaneously the trousers and skirts are not dressed. The constrained conditions essentially needed to give consideration during dressing can be illustrated as follows.

(1) The decoded of $F_4 = 0$ and the decoded of $F_5 = 0$.
(2) The decoded of $F_4 \neq 0$ and the decoded of $F_5 \neq 0$.

The resolution for the problem applied in this study is, firstly, set the two above-mentioned constrained circumstances to check out if there are any chromosomes violating against one of them. When anyone of the above-mentioned circumstance does happen, the fitness of the chromosome is set as '0', representing not available. Otherwise the chromosome is available.

### 3.5 Necessary to Recheck Chromosome

After generations of evolution by GA, several available chromosomes, which are of different values of fitness, can be acquired. Next, we examine the generated chromosomes to check out if there are any corresponding genes of coloring not zero despite of the genes of type not being dressed. The decoded values of those chromosomes that cause the above-mentioned circumstances evaluated through evaluation mechanism (*i.e.*, ANN) will not come up with correct answers of outputs. Under this circumstance, all the corresponding genes for coloring to the genes of types, which are not dressed, should be reset as '0000' for all the original colors (*i.e.*, C, M, Y, and K). In other words, there are four conditions needed for the decoded of each chromosome to check out and shown as follows.

(a) IF (the decoded of $F_1 = 0$) Then (the decoded of $f_{11} = 0$, the decoded of $f_{12} = 0$, the decoded of $f_{13} = 0$, and the decoded of $f_{14} = 0$)
(b) IF (the decoded of $F_2 = 0$) Then (the decoded of $f_{21} = 0$, the decoded of $f_{22} = 0$, the decoded of $f_{23} = 0$, and the decoded of $f_{24} = 0$)
(c) IF (the decoded of $F_3 = 0$) Then (the decoded of $f_{31} = 0$, the decoded of $f_{32} = 0$, the decoded of $f_{33} = 0$, and the decoded of $f_{34} = 0$)
(d) IF (the decoded of $F_4 = 0$) Then (the decoded of $f_{41} = 0$, the decoded of $f_{42} = 0$, the decoded of $f_{43} = 0$, and the decoded of $f_{44} = 0$)

And then take all the decoded of the modified chromosome as the input value of the input nodes for ANN to test again so as to obtain the correct output vector of an available chromosome. Finally, through Eq. (1), the exact fitness of the available chromosome can thus be acquired. Judging from the fitness of chromosome whether approaching closely enough to 1 or not to decide if the solution lives up to the desired apparel styling of the customer can thus be achieved.

## 4. ACQUISITION OF KNOWLEDGE

A neural network consisting of one input layer, one output layer, and one hidden layer is used in the knowledge acquisition of wearing style in this paper. Its construction is illustrated in Fig. 3. The back propagation algorithm [14] is used for data training. Referring to a professional portrait booklet of apparel fashion styling [11], four basic types of fashion styling, *i.e.*, "modern", "elegant", "casual", and "sporty" were adopted. There were 30 styling samples selected for each type of apparel styling from the booklet. Next, each of the 30 selected samples was randomly and equally divided into two sets (*i.e.*, 15 samples for each), training and testing.

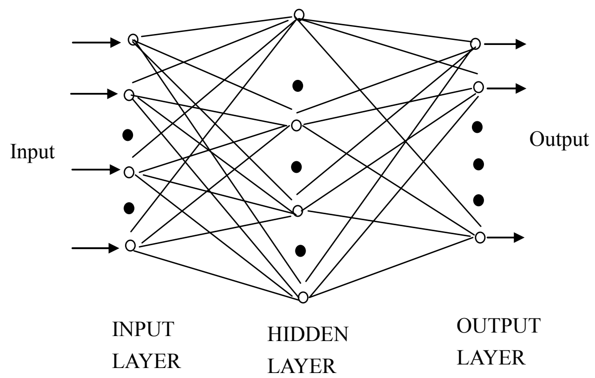



Fig. 3. A multi-layer perception with one hidden layer.

### 4.1 Learning Sets and Testing Sets

There are two basic factors for wearing style, *i.e.*, "type" and "color" applied for apparel styling design in this paper. The coding for the two factors and their attributes are illustrated as Table 1. But for the sake of decreasing the number of input nodes in ANN, we decode the obtained solution (*i.e.*, 00, 01, 10, or 11 for the attributes of type factors; 0000, 0001, 0010, 0011, …, and 111 for those of color factors shown in Table 1) from the search mechanism as input vectors to represent different kinds of clothing wearing style. For example, Fig. 4 shows a model with a modern styling (*i.e.*, expected outcome = 1000), dressed in "odd jacket" (*i.e.*, $F_1 = 0.6667$), "T-shirt" (*i.e.*, $F_2 = 0.6667$), "pleats skirt" (*i.e.*, $F_4 = 1.0000$), but not dressed in vest (*i.e.*, $F_3 = 0000$), and trousers (*i.e.*, $F_5 = 0000$). As for the adopted color tones for each clothing elements mentioned above, we can directly refer to the calibration of color bar to acquire the ones (*i.e.*, C, M, Y, K) of the odd jacket, T-shirt, and pleats skirt as (0, 90, 85, 0), (80, 50, 0, 0) and (85, 50, 20, 10) respectively.

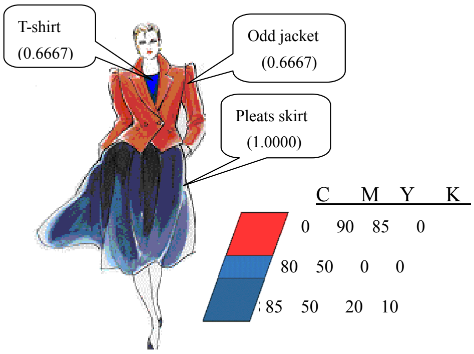



Fig. 4. Illustration of a model with a “modern” styling.

**Table 2. Input vector and output vector for a “modern” styling.**

| Styling sample | Input vector $(F_1^D,F_2^D,F_3^D,F_4^D,F_5^D,f_{11}^D,f_{12}^D,f_{13}^D,f_{14}^D,f_{21}^D,f_{22}^D,f_{23}^D,f_{24}^D,f_{31}^D, f_{32}^D,f_{33}^D,f_{34}^D,f_{41}^D,f_{42}^D,f_{43}^D,f_{44}^D,f_{51}^D,f_{52}^D,f_{53}^D,f_{54}^D)$ | Output vector |
|---|---|---|
| Modern | (0.6667,0.6667,0.0000,1.0000,0.0000,0.00,0.90,0.85,0.00,0.80, 0.50,0.00,0.00,0.00,0.00,0.00,0.00,0.85,0.50,0.20,0.10,0.00, 0.00,0.00,0.00) | (1, 0, 0, 0) |

$F_1^D$~$F_5^D$: the decoded of $F_1$~$F_5$ $f_{11}^D$~$f_{54}^D$: the decoded of $f_{11}$~$f_{54}$

Before taking values of the color bar as input values, each of CMYK value was divided by 100 to limit its value to the range of [0,1]. An input vector (0.6667, 0.6667, 0.0000, 1.0000, 0.0000, 0.00, 0.90, 0.85, 0.00, 0.80, 0.50, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.85, 0.50, 0.20, 0.10, 0.00, 0.00, 0.00, 0.00) for the modern styling sample can thus be obtained. There are four sets of apparel styling targets in this study, including Modern, Elegant, Casual, and Sporty. Each of them is encoded with 4-bit gene string, *i.e.*, 1000, 0100, 0010, and 0001 respectively. Therefore, the 4-bit gene string, *i.e.*, 1000, representing the “modern” styling is utilized as the target output vector for output nodes of ANN during learning. The training and testing sets, consisting of input vector and output vector for the example of a modern styling shown in Fig. 4 are illustrated as Table 2.

### 4.2 Training of the Neural Network

The major training steps of back propagation algorithm are as follows [14]: (a) Initialize all the values of connection weight ($W_{ij}$s) between node $j$ in the upper layer and node $i$ in the layer below. (b) Present an input for each node in the input layer and specify the desire output for each node in the output layer. (c) Calculate actual outputs of all the nodes using the present value of $W_{ij}$s. The output of node $j$, denoted by $Y_j$, is a nonlinear function (called a sigmoid function) of its total input.

$$Y_j = \frac{1}{1+e^{-net_{ij}}} \tag{2}$$

where $net_{ij} = \sum_i Y_i W_{ij}$. (d) Find an error term for each output node and hidden node. If $d_j$

and $Y_j$ stand for desired and actual values of a node, respectively, for an output node,

$$\delta_j = (d_j - Y_j)Y_j(1 - Y_j), \tag{3}$$

and for hidden layer node,

$$\delta_j = Y_j(1 - Y_j)\sum_k \delta_k W_{ij}, \tag{4}$$

where $k$ is over all nodes in the layer above node $j$. (e) Update weights by

$$W_{ij}(t + 1) = W_{ij}(t) + \alpha\delta_j Y_i + \gamma(W_{ij}(t) - W_{ij}(t - 1)), \tag{5}$$

where $W_{ij}(t)$ stands for connection weight value between node $j$ in the upper layer and node $i$ in the layer below, $\alpha$ is a learning rate, and the momentum factor $\gamma$ is a constant between 0 and 1. (f) Return to step (b) to present another new input for each node until all the training sets have been learned and the weights have stabilized.

## 5. THE EXPERIMENT AND RESULTS

### 5.1 Design Demand

In this session we apply the developed system to a seasonal product planning to help the designer to create an innovative wearing style. Supposed that there is a fashion topic demand, which is of the sense of some kinds of styling fashion on completely "casual" and with a little "sporty", required by the customer. Through the assistance of the search mechanism, a designer can obtain several solutions to realize the abstract demand for some kinds of fashion styling on completely "casual" and with a little "sporty" using weight vector such as (0, 0, 1, 0.6). The applied design example, whose constrained conditions and required demands mentioned above, are illustrated as Table 3.

**Table 3. Set target, known conditions and constrained conditions.**

| Example | Known conditions & Set target | | Constrained conditions |
| --- | --- | --- | --- |
| Apparel styling design | Demand | | The followings are forbidden:<br>(1) (the decoded of $F_4 = 0$) and (the decoded of $F_5 = 0$)<br>(2) (the decoded of $F_4 \neq 0$) and (the decoded of $F_5 \neq 0$)<br>where<br>$F_4$: type factor of "skirt"<br>$F_5$: type factor of "trousers" |
| | Linguistic expression | Quantity vector Expression | |
| | Completely "casual" and with a little "sporty" | (0, 0, 1, 0.6) | |

### 5.2 The Created Results

The key parameters consisting of population size, crossover rate needs to be defined first developing GA computer programs. A theory that can concisely guide the assignment of these values is rarely seen [15]. Initially, the population size, crossover rate and mutation rate were adopted as 10, 0.5 and 0.03 respectively in this research. Firstly, there were totally 10 chromosomes randomly generated one by one during proceeding with the search process. Secondly, the fitness value for each of the generated chromosome will be obtained through both the evaluating of the ANN classifier and the calculation of Eq. (1). After the 1st generation in search process, the best approximate solution for wearing combination can be acquired and illustrated as Table 4.

### 5.3 Modifying the Generated Chromosome

Among these 10 chromosomes listed in Table 4, there are not any case such as simultaneously dressing both or none of the trousers and shirts. Nevertheless, there is the case that the corresponding genes of coloring are not zero despite of the genes of type being not dressed for all the ten chromosomes. Therefore, we should modify those decoded value of genes of coloring not to be zero but the genes of the corresponded genes of pattern being not dressed (*i.e.*, the encoded is “0”) with zero to obtain a more appropriate chromosome (*i.e.*, solution) for practical use. For instance, in the fifth chromosome, whose fitness is as high as 0.8501 shown as Table 4, it is not the case that both the decoded value of the “coat” gene and that of the “trousers” gene of coloring are the same as not to be zero (*i.e.*, the decoded values of CMYK for “coat” and “trousers” are (0.87, 0.33, 0.93, 0.80) and (1.00, 0.47, 0.40, 0.87) respectively) despite of the genes of “coat” type and “trousers” type being not dressed (*i.e.*, $F_1 = 0$ and $F_5 = 0$). Therefore, we modify the decoded values of CMYK for “coat” and “trousers” from (0.87, 0.33, 0.93, 0.80) and (1.00, 0.47, 0.40, 0.87) to (0.00, 0.00, 0.00, 0.00) and (0.00, 0.00, 0.00, 0.00) so as not to violate the conditions mentioned above. Next, we take the reformed decoded 25 parameters as the input values of the input nodes for ANN to re-test so as to obtain the accurate output vector to calculate the fitness correctly with Eq. (1). Thus, a recalculated fitness of the fifth chromosome can be obtained as 0.4821. Table 5 shows the four recalculated results, *i.e.*, No. 1, No. 7, No. 8, and No. 10, whose fitness values are larger than 0.5 as 0.7022, 0.6976, 0.7009, and 0.7037 respectively, can be selected as templates of fashion styling design for the target demand of “completely casual” with “a little sporty”.

### 5.4 Illustrations of Costume for Solutions

Both the illustrations and fitness of the modified chromosomes can be effectively displayed on a monitor for comparison by using display module of the system. Each generated chromosome (*i.e.*, solution), the types and their colors included, is illustrated by both type and color together as coat, shirt, vest, skirt, and trousers from left to right in each row. Besides, the fitness of each solution is shown to the end of each row. Through displaying the illustrations with both type and color together included for each chromosome on the monitor, the wearing senses of chromosomes can be far easier compared with one another. According to the value of fitness, a user can select some good solutions of wearing styling with fitness closer to 1 to refer.

Furthermore, In accordance with the 25 acquired parameters of each chromosome, the illustration for the combinations of all the clothing elements can be accomplished with the commercial CAD software such as Photoshop or CorelDraw tool kits. Fig. 5

**Table 4. Results of the first generation.**

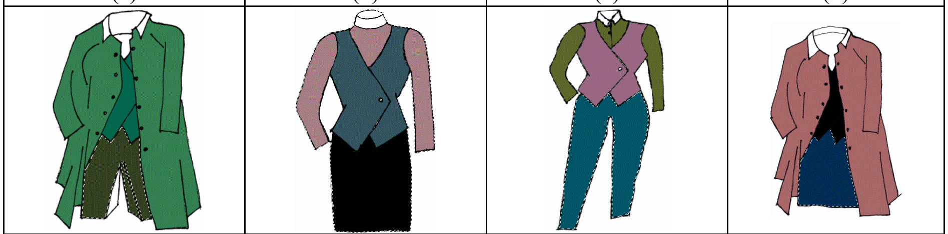
| | | |
|---|---|---|
| 1 | chromosome | 10001011100111000110110011100001001011011010011011010100001000111011010110000101000011000 1 |
| | Input vector | 0.3333 0.0000 1.0000 0.3333 0.0000 0.67 0.00 0.73 0.40 0.47 0.27 0.53 0.67 0.87 0.27 0.73 0.33 0.13 0.00 0.60 0.87 0.53 0.60 0.73 0.53 |
| | fitness | 0.6953 |
| 2 | chromosome | 0010100011101100010001010100011100101000000100100000011110010110110001100100010101 0001001 |
| | Input vector | 0.3333 0.6667 0.0000 0.0000 0.3333 0.33 0.27 0.40 0.80 0.40 0.60 0.47 0.00 0.13 0.07 0.53 0.13 0.47 0.27 0.33 0.27 0.80 0.93 0.53 0.13 |
| | fitness | 0.3453 |
| 3 | chromosome | 00101000111011000110010101000111001010000001001001000111110010110110000100100010101 0001001 |
| | Input vector | 0.3333 0.6667 0.0000 0.0000 0.3333 0.33 0.27 0.13 0.80 0.40 0.60 0.47 0.27 0.13 0.07 0.53 0.13 0.47 0.27 0.33 0.40 0.80 0.93 0.53 0.13 |
| | fitness | 0.2940 |
| 4 | chromosome | 011010110001001000010011001110011100110000100101011110011111111001000000101110111100 00010 |
| | Input vector | 0.6667 0.0000 0.0000 0.0000 1.0000 0.73 0.73 0.00 0.27 0.93 1.00 0.60 0.47 0.33 0.13 0.80 0.80 0.60 0.20 0.20 0.07 0.13 0.07 0.73 0.40 |
| | fitness | 0.6958 |
| 5 | chromosome | 110101100111111110001010111100010101011110001000011000100100100011001110010111010010 11100 |
| | Input vector | 0.0000 1.0000 1.0000 0.6667 0.0000 0.87 0.33 0.93 0.80 0.53 0.27 0.13 0.40 0.53 0.53 0.47 0.33 0.07 1.00 0.67 0.53 1.00 0.47 0.40 0.87 |
| | fitness | 0.8501 |
| 6 | chromosome | 011010110001000000001001110111001100010000010110101111001110111100100000101110111100 00011 |
| | Input vector | 1.0000 0.0000 0.0000 0.0000 1.0000 0.73 0.73 0.00 0.27 0.93 0.87 0.60 0.47 0.87 0.13 0.53 0.53 0.60 0.73 0.20 0.07 0.00 0.07 0.73 0.40 |
| | fitness | 0.3493 |
| 7 | chromosome | 100001110101110111110011011110010101011110001100011000100101000011001110010111010010 11100 |
| | Input vector | 0.0000 1.0000 1.0000 0.6667 0.0000 0.87 0.33 0.93 0.80 0.00 0.33 0.13 0.40 0.80 0.53 0.47 0.33 0.60 0.47 0.20 1.00 0.87 0.33 0.47 0.53 |
| | fitness | 0.7017 |
| 8 | chromosome | 010101100111111110101011110001110001010110010110101010110001001101001100111000110100 10100 |
| | Input vector | 0.0000 0.3333 1.0000 0.0000 0.3333 0.20 0.93 0.80 0.27 0.20 0.07 0.73 0.67 0.40 0.60 0.33 0.07 0.47 0.80 0.73 0.67 1.00 0.47 0.40 0.33 |
| | fitness | 0.8503 |
| 9 | chromosome | 011010110001000000001001100111001100011000010110101111001110111100101000010111011110 00010 |
| | Input vector | 0.6667 0.0000 0.0000 0.0000 1.0000 0.73 0.73 0.00 0.33 0.93 0.87 0.60 0.47 0.87 0.13 0.80 0.53 0.60 0.20 0.20 0.07 0.00 0.07 0.73 0.40 |
| | fitness | 0.6802 |
| 10 | chromosome | 000111100111100010000011101111101111110110101111110101010100100111101001000010 10001 |
| | Input vector | 0.3333 0.0000 1.0000 0.6667 0.0000 0.27 0.67 0.47 0.13 0.60 0.67 0.67 1.00 0.33 0.73 0.87 1.00 0.93 0.73 0.20 0.53 0.53 0.47 0.93 0.07 |
| | fitness | 0.6588 |

Population: 10 Chromosome: 89bits Generation: 1 Crossover probability: 0.5 Mutation probability: 0.033

**Table 5. Modified results of the first generation with fitness more than 0.5.**

| | | |
|---|---|---|
| 1 (✓) | chromosome | 1000101110011100011011001110000100101101101001101101010000100011101101011 0000101000011000 1 |
| | Input vector | 0.3333 $\boxed{0.0000}$ 1.0000 0.3333 $\boxed{0.0000}$ 0.67 0.00 0.73 0.40 $\boxed{0.00\ 0.00\ 0.00\ 0.00}$ 0.87 0.27 0.73 0.33 0.13 0.00 0.60 0.87 $\boxed{0.00\ 0.00\ 0.00\ 0.00}$ |
| | fitness | 0.7022 |
| 7 (✓) | chromosome | 1000011101011101111100110111100101010111100011000110001001010000110011100 1011101001011100 |
| | Input vector | $\boxed{0.0000}$ 1.0000 1.0000 0.6667 $\boxed{0.0000}$ $\boxed{0.00\ 0.00\ 0.00\ 0.00}$ 0.00 0.33 0.13 0.40 0.80 0.53 0.47 0.33 0.60 0.47 0.20 1.00 $\boxed{0.00\ 0.00\ 0.00\ 0.00}$ |
| | fitness | 0.6976 |
| 8 (✓) | chromosome | 0101011001111111101010111100011100010101100101101010101100010011010011001 1100011010010100 |
| | Input vector | $\boxed{0.0000}$ 0.3333 1.0000 $\boxed{0.0000}$ 0.3333 $\boxed{0.00\ 0.00\ 0.00\ 0.00}$ 0.20 0.07 0.73 0.67 0.40 0.60 0.33 0.07 $\boxed{0.00\ 0.00\ 0.00\ 0.00}$ 1.00 0.47 0.40 0.33 |
| | fitness | 0.7009 |
| 10 (✓) | chromosome | 0001111001111000100000111011111011111101101101011111101010101001001001111 0100100001010001 |
| | Input vector | 0.3333 $\boxed{0.0000}$ 1.0000 0.6667 $\boxed{0.0000}$ 0.27 0.67 0.47 0.13 $\boxed{0.00\ 0.00\ 0.00\ 0.00}$ 0.33 0.73 0.87 1.00 0.93 0.73 0.20 0.53 $\boxed{0.00\ 0.00\ 0.00\ 0.00}$ |
| | fitness | 0.7037 |

Population: 10 Chromosome: 89bits Generation: 1 Crossover probability: 0.5 Mutation probability: 0.033



| (a) | (b) | (c) | (d) |
|---|---|---|---|
| Coat + Vest + Pant skirt | High-necked blouse + Vest + Tight skirt | Shirt + Vest + AB trousers | Coat + Vest + Tight skirt |

Fig. 5. Illustrations of costume for solutions (chromosomes) matched with demand (a) No. 1 (b) No. 7 (c) No. 8 (d) No. 10.

shows illustrations of No. 1, No. 7, No. 8, and No. 10 drawn and painted with Photoshop. A kind of "casual" is the so-called coordinate or separate that consists of two or more items of apparel with the same or contrasting fabrics, colors, patterns, and trimmings, which are together for joint sales in the market [16]. For instance, jackets and skirts (*e.g.*, No. 1 and 10), shirts and jeans (*e.g.*, No. 8), skirts and pullovers (*e.g.*, No. 7) may be coordinated. According to the professional view mentioned above, the generated solutions are all well in accordance with the perception of "casual". Moreover, colors connect with human sentiment [17], *e.g.*, green connects with fresh and safe; blue is with quiet and bright; red is with passionate and warm. The colors of garments for them all are of tones of green, blue, and red, which are linked with "fresh & safe"; "quiet & bright"; and "passionate & warm" respectively. Thus, it is proved that the obtained solutions (*i.e.*, No. 1, No. 7, No. 8, and No. 10) go pretty well with the needed wearing style of "completely casual with a little sporty".

## 6. CONCLUSIONS

This paper proposed a GA based approach to create innovative design schema to improve the inspiration to the designer. Through the assistance of this developed conceptual design system, a salesperson can easily acquire innovative apparel styling solutions as references like a consultant to give suggestions of apparel styling more smoothly. Besides, it can be applied as a computer-aided professional skill-training tool for the employee of apparel industry. The color texture is related to both the material and the color of the fabric. However, in this paper only the simple color types are concerned with. We are now trying to extend our solution model to be even more available for color textures. In addition to the application aspect of apparel styling design, this intelligent system can also be implemented to other product design by changing the methodology of coding in accordance with different design factors and attributes. Through the developed intelligent computer aided system and its implementation, it is accomplished that a computer is no longer just to play limited rolls of a machine for feature drawing, shape simulation and data storing, but furthermore can be a supplier of creative inspirations and professional expertise.

## REFERENCES


1. D. Ujević, D. Rogale, and D. Tržić, "Development and application of computer support in garment and technical textile manufacturing processes," *Tekstilec*, Vol. 51, 2002, pp. 224-229.
2. H. Rödel, S. Krzywinski, A. Schenk, and C. Herzberg, "Links between design, pattern development and fabric behaviours for cloths and technical textiles," *Tekstilec*, Vol. 44, 2001, pp. 197-202.
3. T. Sano and H. Yamamoto, "Computer aided design system for Japanese kimono," *IEEE Instrumentation and Measurement Technology Conference*, Vol. 1, 2001, pp. 326-331.
4. S. Inui, "A preliminary study of a deformable body model for clothing simulation," *International Journal of Clothing Science and Technology*, Vol. 13, 2001, pp. 339-350.
5. Z. G. Luo and M. M. F. Yuen, "Reactive 2D/3D garment pattern design modification," *CAD Computer Aided Design*, Vol. 37, 2005, pp. 623-630.
6. Y. Cho, N. Okada, H. Park, M. Takatera, S. Inui, and Y. Shimizu, "An interactive body model for individual pattern making, *International Journal of Clothing Science and Technology*, Vol. 17, 2005, pp. 100-108.
7. N. Mori, "Application of Kansei-engineering to design," *Journal of The Society of Fiber Science and Technology*, Vol. 51, 1995, pp. 227-232.
8. T. Fukuda, T. Chikazawa, Y. Hasegawa, F. Kobayashi, K. Shimojima, and Y. Yamaguchi, "Sensory evaluation system based on KANSEI self-tuning spline fuzzy in-

ference (Acquisition of KANSEI for Persimmon)," *International Journal of Fuzzy Systems*, Vol. 2, 2000, pp. 54-59.
9. D. E. Goldberg, *Genetic Algorithms in Search*, *Optimization & Machine Learning*, Addison-Wesley, New York, 1989.
10. S. B. Kaiser, *The Social Psychology of Clothing*, *Symbolic Appearance in Context*, 2nd ed., Macmillan, New York, 1990.
11. K. Kochilon, *Fashion & Color*, Han-Dan Publishing Co., Taipei, 1990.
12. P. V. Ulrich, L. J. Anderson-Connell, and W. Wu, "Consumer co-design of apparel for mass customization," *Journal of Fashion Marketing and Management*, Vol. 7, 2003, pp. 398-412.
13. D. Hearn and M. P. Baker, *Computer Graphics*, 2nd ed., Prentice Hall, Inc., New York, 1994.
14. M. M. Nelson and W. T. Illingworth, *A Practical Guide to Neural Nets*, Addison-Wesley Publish Co., New York, 1991.
15. M. Srinivas and L. M. Patnaik, "Genetic algorithms: a survey," *Computer*, Vol. 27, 1994, pp. 17-26.
16. M. A. V. Rocha, L. Hammond, and D. H. Hawkins, "Age, gender and national factors in fashion consumption," *Journal of Fashion Marketing and Management*, Vol. 9, 2005, pp. 380-390.
17. J. Sun, "Emotional expression in clothing beauty," *Journal of Tianjin Polytechnic University*, Vol. 24, 2005, pp. 81-84.

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