International Journal of Computational Intelligence Systems, Vol. 7, Supplement 2 (July 2014), 74-84

Application of Interactive Genetic Algorithm based on hesitancy degree in product configuration for customer requirement

Runliang Dou*
College of Management and Economics, Tianjin University, Tianjin, P.R. China

Chao Zong
Graduate, College of Management and Economics, Tianjin University, Tianjin, P.R. China
Email: zongchao@ tju.edu.cn
www.tju.edu.cn

Received 3 November 2013

Accepted 10 March 2014

Abstract

With significant impact on the personalized product configuration, Interactive Genetic Algorithm is introduced to respond to customer requirement. For the user could conveniently design their favorite product and interact with the system by a graphical interface, the car console conceptual design system is established. And IGA based on hesitancy degree is proposed in this paper to reduce user's uncertainty or fuzzy feeling. By repeating the simulation experiment, the results validate the effectiveness of the proposed method in this paper.

Keywords: Hesitancy Degree; Interactive Genetic Algorithm; Customer oriented; Product Configuration

1. Introduction

With the rapid development of the market economy, many companies have begun to focus on their ability to quickly respond to customer demands and to design customer-oriented products[1-3]. Market competition requires product designers and manufacturers to pay increasing attention to their customers' personalized requirements. To gain market share, they need to supply the global market with various kinds of customized products within a short period of time. Configuration of customized products means swift and accurate response to customers' personalized demands, and the application of modular design, manufacturing and configuration is one of the strategies to respond to customer demands. Although traditional product configuration methods can produce feasible product configuration solutions, that approach fails to customize a product based on personalized demands. Thus the first step in product configuration is to quickly identify customers' real-time needs and translate them into corresponding product functions. Customer's personalized demands can be classified into two types: technical requirements and non-technical requirements. Non-technical requirements often manifest as implicit parameters in the algorithm, and the moderation of implicit parameters requires frequent interaction with customers. The Interactive Genetic Algorithm (IGA) is introduced for this purpose.

IGA, also known as the Human-Computer Interactive Evolutionary Optimization Algorithm, is an evolutionary algorithm treating human subjective evaluation as the individual fitness value[4]. In the evolutionary computation process, users control and guide the evolution process through human-computer interaction (HCI) based on individual needs. The most prominent characteristic of IGA is the integration of human intelligence into the evaluation process, which takes the Genetic Algorithm one step further by allowing the individual fitness value to be decided by the user rather than by evaluating functions. IGA provides an effective solution to the optimization of implicit parameters, thus facilitating the application of traditional genetic algorithms to a wider range of fields. Many domestic and international experts have done a great deal of research and innovation in the field. Rodriguez and his team proposed using IGA to design the surface color of buildings. They constructed a user-preferred color scheme by combining the algorithm with a neural network to lower user fatigue[5]. Takekata, Li and colleagues used IGA to process images to satisfy users' emotional and psychological needs to meet users' demands[6-7]. Rho and others used Interactive Genetic Algorithm to process voice [8-9] and design a music information query system which provides user with a satisfying sorting function based on user reaction to rhythm parameter. IGA can also be used in autonomous learning. Nishino has successfully applied IGA to interactively learning how to draw 3D computer images. Users can learn how to draw 3D images and can hone drawing skills through interacting with the interactive learning system[10]. Lewis was the first one to apply IGA to control engineering and Suga and his team took it further to use the algorithm in robot control. By designing a robot's facial expressions, communicative ability and behavioral preferences through IGA, they were able to achieve the personalization of the robot and enable its quick adaptation to an environment [11-12]. IGA enjoys an even wider popularity in industrial product design and art creation. Any design process requires the participation of the designer, and IGA can not only assist designers with the design process by sharing the workload, but also serve to inspire. Byrne and colleagues applied IGA directly to the product design process, which allowed users to participate in man-machine conversation through a friendly interface and input and modify pre-existing designs. This effectively lightened the user burden of providing feedback[13]. Kowaliw and his team focused their research on how to stimulate user creativity with IGA solutions to design particularly novel and personalized products[14]. DI PIETRO and his team adopted a noise compensation strategy[15-16] to reduce noise in evolutionary algorithms and averaged samples to improve genetic operators.

As mentioned above, there have been great developments in the application of and theoretical research on IGA. However, with new developments come new problems: first, users assign a specific value to an estimated individual fitness, but given cognitive discrepancy, elements of uncertainty like fuzzy random variables remain. Second, most of the research carried out so far adopts the method of constructing an agent-based user cognition model to replace the user in the evaluation of part or even all individuals through knowledge acquisition and machine learning. This process of cognition model construction through supervised learning hardly addresses the question of how to make the learning process more focused and effective. Third, the evolutionary process and results are constantly affected by the user's psychological state, especially by user hesitancy. This leads to significant uncertainties in user evaluation, and introducing other variables to denote individual fitness value would only create new problems of user fatigue.

Taking the above-mentioned problems into consideration, we have discovered in our research that the key to solving these problems lies in the investigation of the user's psychological experience during the evaluation of the evolution process and the influence of the user's psychological changes on evolutionary noise. IGA is used to evaluate individual fitness based on personal preference, and the user's changing psychological experience and product-related preference will certainly affect the evolution process and result. Since the user's comprehension of the evolutionary population is not clear enough, especially in the initial stages of evolution, they are easily affected by existing noise and develop feelings of ambiguity and uncertainty. We call such feelings of ambiguity and uncertainty "hesitancy".

In this paper, a hesitancy-based IGA is proposed to solve this problem. By investigating the impact of the user's emotional fluctuations on individual fitness values during the evolution process, as well as hesitancy developed from uncertainty regarding the evolutionary population, we have established a hesitancy adjustment mechanism which based on the hesitant fuzzy sets[17-18] to lower noise and applied an artificial neural network and layered IGA to speed up population convergence and further decrease user fatigue. Finally, we carried out a simulation experiment where we applied the method proposed in this paper to the evolutionary design system for car consoles. The result verifies the validity of our argument that the method proposed is effective in lowering noise, shortening evaluation time and reducing user fatigue. It also demonstrates that the proposed hesitancy-based IGA shows promise when applied to the configuration of customized products.

2. Interactive Genetic Algorithm Based on hesitancy degree

As all known, the fitness value of every individual on their evaluation is defined by users in IGA, rather than calculated by a given fitness function. Therefore, IGA could be separated into two modules: user evaluation modular and population evolution modular. In IGA, the user evaluation modular corresponds to the fitness value computing modular in traditional genetic algorithm. In particular, user could realize man-machine interaction by graphic interface; then, users' personalized cognition and preference make them providing the fitness value of evolutionary individual through interactive interface. Population evolution modular realizes individual evolution process by computer, including population initialization, encoding, decoding and corresponding evolutionary operator, such as cross recombinant, mutation and so on. The above two modules interact until user finds out their satisfied individual. The algorithm can be vividly stated in fig.1. , and its flow chart is shown in fig.2. .

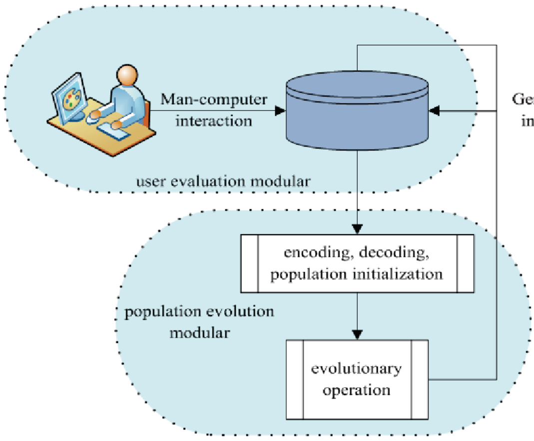

Fig.1. Schematic Diagram of Interactive Genetic Algorithm

2.1. *The concept of hesitancy degree*

The most prominent feature that distinguishes Interactive Genetic Algorithm greatly from traditional genetic algorithm is that the individual fitness value is evaluated in accordance with human cognition and preference, rather than computed by function. However, human cognition could change along as they gain more and more knowledge about the subject, that is to say, because of human subjective factor and the increase of their fatigue, they may give different fitness value to the same individual in different evaluation stage, i.e. deviation or noise.

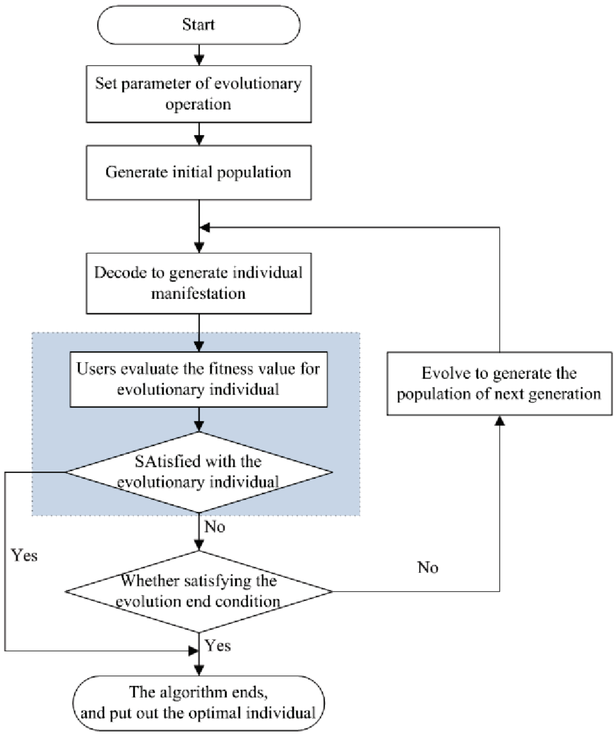

Fig.2. Traditional IGA

Getting more and more knowledge about evolutionary individual, the users' cognition gradually develops from the fuzzy stage to relatively clear one. We divide the evaluation process into three stages: cognitive stage, middle stage and fatigue stage.

User cognition about evolutionary individual gradually goes over into relatively clear stage from very fuzzy one. When user is initially exposed to evaluation system, they are in the cognitive stage of the evaluation process, and they have fuzzy evaluation about evolutionary individual; which causes deviation, i.e. noise, between evaluated and individual's real fitness value. At the moment, however, the main reason to cause noise is that user's cognition about the evolutionary individual is so fuzzy that they are not clear about their ideal individual. Their confused feeling about ideal individual is regarded as hesitancy degree in user psychology. Thus, when users evaluate individual, hesitancy degree will vary along with their cognition about the individual gradually deepens. In the cognitive stage of the evaluation process, they are not clear about the ideal individual, at the moment, their feeling of hesitancy is much stronger; when their cognition about the evolutionary individual increase, and the ideal individual occurs; now their feeling of hesitancy is much weaker. Thereby, the intensity of the hesitant feeling of the i^{th} individual $x_i(t)$ in the t^{th} generation can be demonstrated by hesitancy degree in the following Eq. (1)

$$h(t) = \frac{1}{n_g}\sum_{j=1}^{n_g} \alpha\left(T_i(t), T_j(t)\right) + \frac{T_i(t) - \bar{T}(t)}{\bar{T}(t)} \tag{1}$$

In which,

$$\alpha\left(T_i(t), T_j(t)\right) = \begin{cases} T_i(t) - T_j(t), T_i(t) > T_j(t) \\ 0, \qquad\qquad T_i(t) \le T_j(t) \end{cases}$$

$$\bar{T}(t) = \frac{1}{n_g}\sum_{j=1}^{n_g} T_j(t)$$

In the function (1), n_g stands for the account of the t^{th} generation; $T_i(t)$ means the evaluation time of the i^{th} individual $x_i(t)$ in the t^{th} generation, accordingly and $T_j(t)$ the evaluation time of the j^{th} individual $x_j(t)$ in the t^{th} generation. $\alpha\left(T_i(t), T_j(t)\right)$ is a piecewise function. If $T_i(t) > T_j(t)$, the resolved value means the evaluation time difference between evolutionary individual $x_i(t)$ and $x_j(t)$, and $\bar{T}(t)$ the average evaluation time of the t^{th} generation. The expression of hesitancy degree $h_i(t)$ stands for the average evaluation time of the i^{th} individual $x_i(t)$ in the t^{th} generation among the position of all individual in the current generation and their evaluation time comparison. When $h_i(t) > h_0$, it is deemed users have hesitant feeling about the individual $x_i(t)$, in which h_0 is preset andreflects critical value of hesitancy degree.

The principle of hesitancy degree adjustment mechanism will be detailed on in next part.

2.2. *Principle of hesitancy degree adjustment mechanism*

As user's cognition about evolutionary individual gradually changes from very fuzzy to relatively clear, when user are exposed to evaluation system for the first time, they are in the cognition stage of evaluation, and they have fuzzy evaluation about evolutionary individual. There exists difference, i.e. $f(x_i) \ne f'(x_i)$ between the fitness values $f(x_i)$ estimated by user and the real one $f'(x_i)$ of individual x_i. As to the deviation$|f(x_i) - f'(x_i)|$

If$f(x_i) > f'(x_i)$, user overestimate the evolutionary individual x_i; the equation $f_+ = f(x_i) - f'(x_i)$ is called positive deviation;

If $f(x_i) < f'(x_i)$, user underestimate the evolutionary individual x_i; the equation $f_- = f(x_i) - f'(x_i)$ is called negative deviation;

As users have fuzzy evaluation about evolutionary individual in the stage of cognition, the hesitant individual is generated, which leads to deviation among all the hesitant individuals. How to reduce the positive and negative deviation, f_+ and f_-, and make the individual fitness value $f(x_i)$ closer to the real fitness value $f'(x_i)$ is the key to resolve problem.

The problem to be resolved is described in the following form:

$$max f(x), \qquad x \in S$$

In which, f(x) means the fitness value of evolutionary individual, estimated by user and S the searching room for individual x. As what we known, when user has the hesitancy feeling about individual xi, it is easy for them to offer their estimated fitness value about the individual with positive/negative deviation. Next, the deviation generated by hesitant individual in the fuzzy evaluation will be analyzed.

The concept of genetic significance unit is introduced here. It is all known that each evolutionary individual xi consists of n constituent elementsU_i, and each element $U_i$corresponds to the phenotype of a given modular.

Thus, $\sigma_p(x_i, x_j)$ is deemed as similarity of the constituent element U_p in the evolutionary individuals x_i, x_j in the following:

$$\sigma_p(x_i, x_j) = \frac{1}{|U_p|}\sqrt{\sum_{j_p=1}^{|U_p|}(F_{x_i}(U_p^{j_p}) - F_{x_j}(U_p^{j_p}))^2} \tag{2}$$

Of which, U_p^{jp}denotes allele significance unit ofU_p, $F_{x_i}\left(U_p^{jp}\right)$and $F_{x_j}(U_p^{jp})$respectively the fitness value of the constituent element U_p^{jp} among the evolutionary individuals, $|U_p|$meaning the number of allele significance unit of the constituent element U_p.

And let be,

$$d\left(x_i(t), x_j\right) = \frac{1}{n}\sum_{p=1}^{n}\sigma_p\left(x_i(t), x_j\right) \tag{3}$$

Of which $d\left(x_i(t), x_j\right)$ means the distance between the two evolutionary individuals $x_i(t), x_j$, i.e. the similarity of the constituent elements. Then the distance is applied to get the set consisting of evolutionary individual closer to hesitant individual $x_i(t)$ in the evaluation process, and it is denoted as $S(x_i(t))$. Thus,

$$S(x_i(t)) = \{x_j \mid d(x_i(t), x_j) \leq d_0, x_j \in N_e\} \quad (4)$$

Of which, N_e is the set of the evaluated evolutionary individuals, and d_0 is set up in advance, reflecting the critical value of the distance between two individuals. By computing the average value of the evolutionary individuals in the set:

$$\bar{f}(x_i(t)) = \frac{1}{|S|}\sum_{j=1}^{|S|} f(x_j), x_j \in S(x_i(t)) \quad (5)$$

And figure out the approximate real fitness value of hesitant individual $x_i(t)$

$$\tilde{f}'(x_i(t)) = \frac{f(x_i(t)) + \bar{f}(x_i(t))}{2} \quad (6)$$

By adjusting $\tilde{f}'(x_i(t))$, user's fuzzy evaluation value of individual $x_i(t)$, work out

$$f(x_i(t)) = \tilde{f}'(x_i(t))$$

It is all-known that user's cognition about evaluation individual is featured by fuzziness and gradualness. Because of the existing fuzziness, in the cognition stage of the evaluation process, it is easy for user to evaluate evolutionary individual with positive/ negative deviation. Thereby, hesitancy degree adjustment mechanism is put forward to reduce f_+ and f_-, and to make individual fitness value $f(x_i)$ closer to the real fitness value $f'(x_i)$. Firstly figure out the individual user has hesitancy to, then find out its similar evolutionary individual by computation, and finally use the fitness value of its similar individual to estimate its approximate real fitness value $\tilde{f}'(x_i(t))$, and assign it to the hesitancy individual $x_i(t)$ to get the adjusted fitness value $f(x_i(t))$. Additionally with the feature of gradualness, along with users have more and more knowledge of the evaluation individual, they are more and more certain about the evolutionary individual, and they enter into the steady stage of evaluation process where hesitancy degree adjustment mechanism is not be applied, but directly deeming user's evaluated value as the real value of evolutionary individual.

Obviously, when user evaluates individual, the hesitancy degree adjustment mechanism is used to relieve user's psychological stress, speeds up the algorithm, and reduces user's fatigue to some extent. The specific flow of the algorithm will be discussed in the following.

2.3. *The Treatment of Constraint Dissatisfied Individual and Acceleration of Algorithm and Population Convergence*

As to such complex products like car and mobile phone, when applying IGA to process configuration solution, it is easy to generate unreasonable individual because the presence of constraints; thus, how to avoid the generation of unreasonable individuals is also a key problem bothering IGA. Accordingly, the generated strategy restricting constraint unsatisfied individual is applied in the paper, i.e. the principle of IF-THEN is used. As shown in fig.3. , the generation of initial population is chosen from large-scale population, so it is possible to generate many individual dissatisfying constraint, for which, in accordance with the various constraint condition stored in pre-established constraint database, the rule of IF-THEN is applied in the paper to directly prevent constraint unsatisfied individual appearing in the initial population with no excellent gene decreasing. In the evolutionary process, the individual dissatisfying constraint might be generated in the process of crossover and mutation; in the light of the rule of IF-THEN, the element or modular dissatisfying constraint will be changed into its corresponding one satisfying constraint.

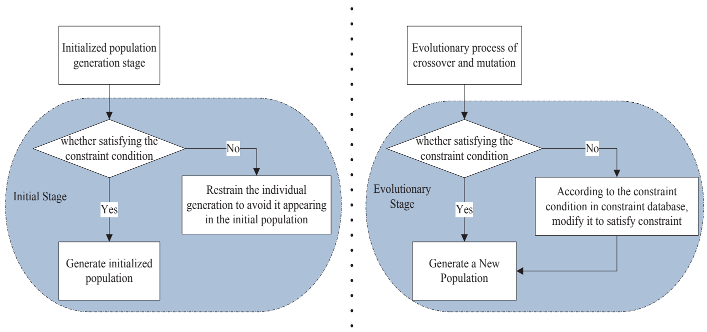

Fig.3. Treatment of individual dissatisfying constraint in different stages

Artificial neural network is a new intelligent information process system simulating human brain neuron feature, and it is characterized by self-adaption, self-organization, fault-tolerant and other good features. By integrating evolutionary algorithm with neural network, the evaluation of the fitness value of evolutionary individuals can be divided into two stages: rough evolutionary stage and precise evolutionary stage. In the former stage, as individuals disperse, and their fitness value greatly differ with large gap, the precision of modular could be not high, and its threshold value could be large in the stage; in the latter stage, individuals tend to convergence, the gap among their fitness value is so small that neural network can't tell out. It is necessary for human to reevaluate the individuals, and their results are deemed as the sample for the neural network to continue learning. It is not hard to see that to use human neural network could drastically lower user's fatigue, however, when artificial neural network evolve to certain generation, the gap in individuals' fitness value becomes smaller and smaller; if the individuals continue to evolve, there will be no significant difference among their fitness value, thus there is no evolution sense. Thereby, layered interactive genetic algorithm is used here: users steer the evolutionary direction and determine gene significance unit satisfying users' preference; the gene significance unit unaccepted by users need further evolution. As shown in fig.4. , they enter into the local searching stage where users are only involved in evaluation for one time; however, the system is able to, at the top speed, generate product satisfying users' preference in next generation or several generation. To use layered interactive genetic algorithm makes the whole system work with more personalized service. It not only well solves the problem of users' fatigue, but also dramatically decreases the number of evolutionary generation, saving the resources of the system and orientating population evolution towards users' anticipation. The specific application is discussed in details in next part.

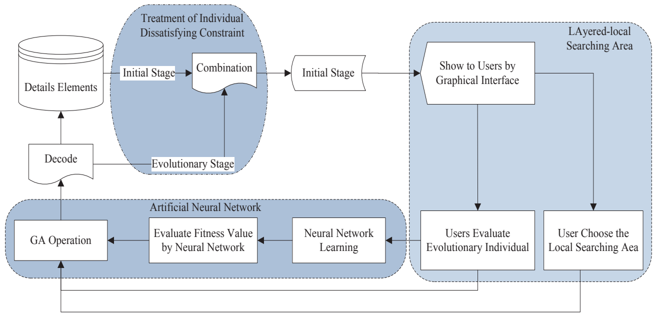

Fig.4. System Flowchart

2.4. *Flow and step of the Algorithm*

In the paper, the traditional IGA has been improved by combining hesitancy degree adjustment mechanism with constraint process methods, and using human neural network and layered interactive genetic algorithm to accelerate population convergence; from fig.5. , it can be seen its specific algorithm flow.

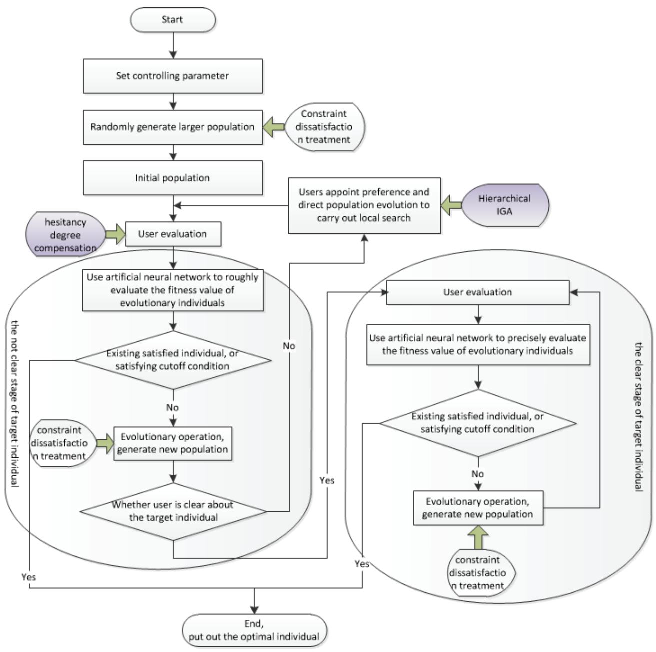

Fig.5. MAN-IGA flowchart

Algorithm Steps:

- Step 1: set controlling parameter for population evolution;
- Step 2: randomly generate larger population and use delete strategy directly delete the individual unsatisfying constraint to get the initial population;
- Step 3: decode and show to user in graphic interface, adopt hesitancy degree adjustment mechanism; users evaluate evolutionary population;
- Step 4: the system applies artificial neural network to evaluate evolutionary individuals in stages. Firstly in the rough stage, user assess whether the individual is satisfied or not; if satisfied, the optimal solution is put out, and the algorithm ends; if not, turn to step 5;
- Step 5; evolve to generate new population; at the moment, the system applies modification strategy to modify the individual dissatisfying constraint;
- Step 6: whether user is clear about the target individual or not; if clear, they are in the clear stage of target individual evaluation, and turn to step 7; if not, users appoint preference and apply layered interactive genetic algorithm, and turn to step 3;
- Step 7: users continue to evaluate individuals; the system applies artificial neural network to evaluate individuals in stages; at the moment, users are in the stage of precise evaluation;
- Step 8: user assess whether the individual is satisfied or not; if satisfied, the optimal solution is put out, and the algorithm ends; if not, turn to step 7.

3. System Design and Application

3.1. *The System Establishment*

The conceptual design system of car console is established to testify the algorithm’s performance.

3.1.1. *Encode Mode*

In the paper, the encoding of car console conceptual design is featured by combinatorial optimization, similarly like knapsack problem: the genes in chromosome consist of a feasible knapsack, in which the number of items is not fixed; the length of chromosome is changeable, and the order of its items is not important. On the basis of performance, the car console is divided into 6 parts, corresponding to the five main modules and a color module. Each module contains its corresponding several phenotypes, and the binary code of each gene stands for a concrete example. In order to facilitate research, the length of changeable chromosome is converted to equal length gene significance unit by completing gene significance unit, with no influence on result. The encoding of console 001001001 stands for the example of the first GPS navigation, DVD sound system and LED of 6 sizes, as shown in Table 1.

Table 1. Partial Constraint of Console

The Module	Coding
Steering wheel	6 bits
The dash board	9 bits
Shift lever	9 bits
Instrument panel	9 bits
Air-condition outlet	4 bits
The color	3 bits

3.1.2 *Constraint Treatment.*

In the paper, the constraint of console is demonstrated by the structure of IF-THEN in Table 2. In the generation process of initial population, if the generated individuals dissatisfy constraint, they will be directly restrained to generate; in the evolutionary process, if crossover and mutation dissatisfy constraint, in the accordance with the various constraint condition stored in constraint database, the element or module dissatisfying constraint is converted into those that satisfying constraint by changing cross and mutation point, or replacing the gene dissatisfying constraint with those satisfying constraint.

Table 2. Partial Constraint of Console

Number	IF	THEN
MU1	Sound Control System=CD	Integrated LED= Screen01 GPS Navigation System=False
MU2	Sound Control System =DVD1	Integrated LED =Screen02 GPS Navigation System =False
MU3	Sound Control System =DVD2	Integrated LED =Screen02 GPS Navigation System =True
WH3	Steering Wheel= Wheel02	Horn Button=HornBut02or03
WH4	Steering Wheel = Wheel03	Instrumental Panel=3
…	…	…

3.1.3 *Parameter Setting*

The number of initial larger-scale population is set as 45, i.e. N_0=45; considering the limit of the time users used to evaluate each generation and the size of display, the number of population in each generation is set as n=9, cutoff evolutionary generation G_0=25, the probability of cross and mutation respectively as 0.8 and 0.07; the fitness value adapts the integer from 0 to 100. The appropriate threshold value of hesitancy degree adjustment mechanism is defined; according to the experimental results, when $d_0=0.7$ and $h_0=0.9$, the convergence works best; therefore, h_0 and d_0 is respectively valued as 1.1 and 0.7.

3.1.4 *Interactive interface*

As shown in fig.6. , the interactive interface of the system in the paper mainly consists of three sections: the individual display area is on the left; the number of population in each generation is 9; users evaluate individuals to realize evolutionary operation and choose out the optimal individual; in the middle display the two individuals of “the optimal individual at present” and “the optimal individual in the last generation” for reference; in the interactive process, after the users are clear about the ideal individual, they could press the button of “target individual is clear ” to end hesitancy degree adjustment mechanism; on the right is the statistical evolutionary information, including the number of evolved generation, the time user used to evaluate and the number of different evaluated individuals.

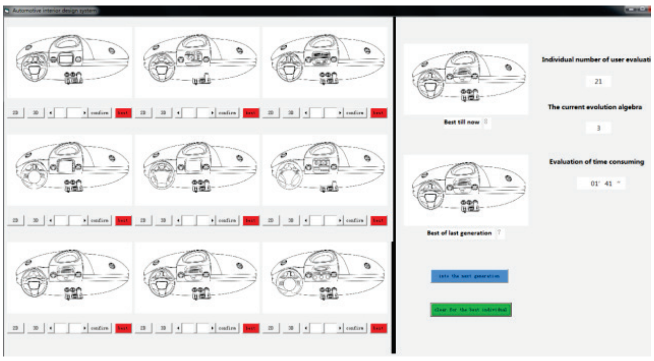

Fig.6. The interactive interface for customization design system of console

3.2. *Result and analysis*

In order to study on the contribution of the method to IGA, the traditional IGA (TIAG) and IGA based on hesitancy degree adjustment mechanism (HAM-IGA) independently operate 20 times, and their results are compared. The operational performance of the two methods is shown in Table 3.

In HAM-IGA, the evolutionary generation and the evaluation time are both better than those in traditional IGA. The average evolutionary generation in HAM-IGA only account for 74.3% that of TIAG, and the evaluation time shortens 31.63%, i.e. when users find out their satisfied solution, their fatigue becomes smaller while their satisfaction about the final evolution increase. In the angle of the different number of evaluated individual, or the diversity of population, it also shows why HAM-IGA work better as the 9 individuals in each generation is mutually different in HAM-IGA.

Table 3. Comparison of operational performance of HAM-IGA and TIGA

Algorithm	HAM-IGA	TIGA
Operation time	20	20
Number of Evolutionary Generation	13.3	17.9
Evaluation Time	9’21”	13’47”
Satisfaction Degree/%	81.86%	69.54%
Evaluating Number of different individual	108.8	132.9
Evaluating Number of the same individual	10.9	28.2
Diversity of Population/%	90.89%	82.50%

What the fig.7. illustrates is the changing curve of the evaluation value given by the user in HAM-IAG and TIGA, in which, ordinate of fitness means the average evaluation value of each generation, abscissa of generation the number of evolutionary generation operated by the system.

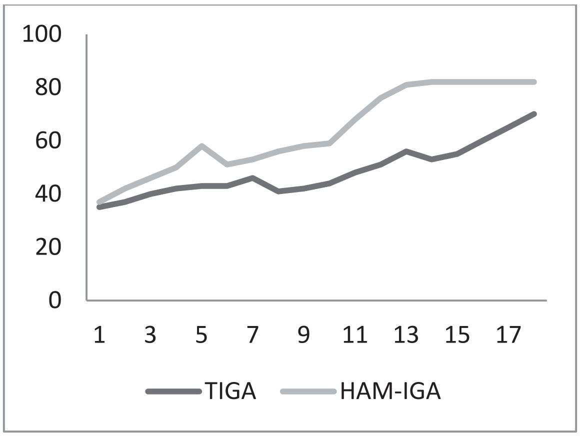

Fig.7. Changing Curve of Evaluation Value

It is easy to see that the average evaluated value in HAM-IAG overall tends to increase, which states the solutions in the searching process are continually close to users' preference; the values in traditional IAG also wholly tend to increase, but the increase range is smaller and full of fluctuation. The main two reasons for the above fact: one the one hand, the evaluation of the individual's fitness value in IGA based on the hesitancy degree adjustment mechanism is more precise and steady, which makes the average evaluation in HAM-IAG overall tends to increase; on the other hand, the layered IGA and IGA based on artificial neural network to evaluate in stages are applied to further accelerate the evolutionary population convergence. While in traditional IGA, users need to give each individual the precise fitness value and usually needs to adjust the nine individuals in an evolutionary generation for many times, which results in great evaluation burden to users and easily causes their fatigue, so that the increase trends of their evaluation value is slow and full of fluctuation. Then the influence of the application of HAM on the system is discussed in Table 4, and finding HAM is used by all the systems applying HAM-IGA before 6.9 generation on average. The result also proves that HAM indeed is able to effectively lower evaluation noise so as to accelerate convergence. Moreover, in the stage when HAM is used, users are not clear about the target individual; while ending to use HAM, it is in the stage that users are clear about the target individual. However, the evaluation time to evaluate each generation in the two stages differs nearly one times, which indicates after users are clear about the target individual, they will evaluate it on purpose; thus the time they use to evaluate each individual decrease. Finally, users' cognitive determination in HAM-IGA and TIGA is compared in fig.8. . When user use HAM-IGA, their cognitive determination significantly changes, and it is much higher and steadier in the stages of evaluation process; while TIGA is used, their cognitive determination does not significantly change, and it is full of fluctuation.

Table 4. The influence of the application of HAM on the system

The stage of HAM	Number of Average evaluation generation	Average operation time	Average evaluation time for each generation
HAM Using Stage	**6.9**	**10'41"**	**1'37"**
HAM Ending Stage	**9.2**	**6'03"**	**0'47"**

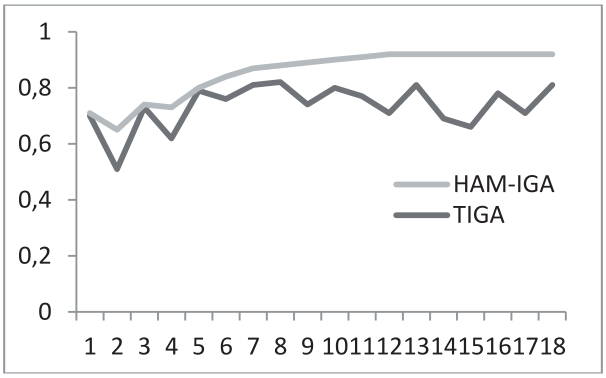

Fig. 8. Comparison of users' cognitive determination in HAM-IGA and TIGA

4. Conclusion

Product configuration for customer requirement has become the trend in market development. In the competitive market of complex product, the product design and manufacturing enterprise began to pay more attention to customer's personalized requirement and be able to globally offer various customized product in a short time. In order to produce the customer oriented product, the interactive genetic algorithm based on hesitancy degree is put forward in the paper. The hesitancy degree adjustment mechanism is established to compensate for the evaluation noise generated for users' hesitancy, and artificial neural network and layered interactive genetic algorithm are applied to accelerate the evolutionary convergence of population. The method proposed in the paper could not only solve users' indetermination and hesitancy for the evolutionary individual which caused by their lack of information in the evaluation stage, but also effectively reduce user fatigue. Then, the conceptual design of car console is chosen as the experimental subject. In accordance with the feature of complexity of car console, the method of constraint treatment in stages is adapted to solve constraint satisfaction in interactive genetic algorithm. In the end, on the basis of the evaluation system of applying the interactive genetic algorithm based on hesitancy degree put forward in the paper to design the conceptual design of car console, by repeating the experiment for many times, and discussing the experimental results, it is verified that the method is able to effectively reduce user's hesitancy degree in the evaluation process, as well as the evaluation noise, and decrease users' evaluation generation and time to avoid their fatigue. In addition, user's satisfaction about the system is also testified, finding the algorithm introduced in the paper is able to effectively increase users' satisfaction about the evolutionary individuals.

The cases of the successful application of the interactive genetic algorithm into various areas demonstrate its valid life. On the basis of previous researches, IGA based on hesitancy is brought forward to process product configuration for customer requirement. To some extent, the method is able to facilitate enterprises to solve the bottleneck problem in the process of product design. In future, we will continue to further specialize on the concept of hesitancy degree and come up with better hesitancy degree adjustment mechanism to better decrease evaluation noise and increase user's satisfaction.

Acknowledgements

The work was supported by the National Science Fund for Interactive Collaborative Optimization of Complex Products Configuration Design for Mass Customization (Grant No. 71201115). The authors are very grateful to all anonymous reviewers whose invaluable comments and suggestions substantially helped improve the quality of the paper.

References

1. Jiao, J., Zhang, Y., Helander, M., A Kansei mining system for affective design [J]. Expert Systems with Applications, 2006, 30(4): 658–673.
2. Petiot, J.-F., Yannou, B., Measuring consumer perceptions for a better comprehension, specification and assessment of product semantics [J]. International Journal of Industrial Ergonomics, 2004, 33(6): 507–525.
3. Seongah Chin, Kyoung-Yun Kim. Facial configuration and BMI based personalized face and upper body modeling for customer-oriented wearable product design [J]. Computers in Industry, 2010.8, 61(6):559-575.
4. Takagi H. Interactive evolutionary computation: Fusion of the capabilities of EC optimization and human evaluation [J]. Proc of the IEEE, 2001, 89(9): 1275-1296.
5. Rodriguez L, Diago L, Hagiwara I. Interactive genetic algorithm with fitness modeling for the development of a color simulation system based on customer's preference [J]. Japan Journal of Industry and Application Mathematics, 2011, 28:27-42.
6. Takekata K, Azmi M, Nishino H. An intuitive optimization method of haptic rendering using interactive evolutionary computation [C]. Proceedings of IEEE International Conference on Systems, Man, and Cybernetics, 2005: 1896-1901.
7. Li Q, Nakamura T, Chao Y, et al. Image color transfer with region matching based on IEC [C]. Proceedings of the IEEE Congress on Evolutionary Computation, 2005: 1501-1508
8. Rho S M, Hwang E J, Kim M K. Music information retrieval using a GA-based relevance feedback [C]. Proceedings of International Conference on Multimedia and Ubiquitous Engineering, 2007:739-744.
9. Takagi H, Ohsaki M. Interactive evolutionary computation-based hearing aid fitting [J]. IEEE Transactions on Evolutionary Computation, 2007, 11(3): 414-427.
10. Nishino H, Iwakiri Y, Sueyoshi T, et al. A network sharable graphics education aid based on interactive evolutionary computation [C]. Proceedings of IEEE International Conference on Systems, Man, and Cybernetisc,2005:1902-1907.
11. Suga Y, Ikuma Y, Nagao D, ed al. Interactive evolution of human-robot communication in real world [C]. Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005:1198-1203.
12. Moshaiov A, Avigad G. Concept-based interactive evolutionary computation for multi-objective path planning [C]. Proceedings of the 2nd IEEE International Conference on Computation Cybernetics, 2004: 115-120.
13. Byrne J, Hemberg E, Brabazon A, A local search interface for interactive evolutionary architectural design [J]. Lecture Notes on Computer Science, 2012, 7247:23-34.
14. Kowaliw T, Dorin A, McCormack J. Promoting creative design in interactive evolutionary computation [J]. IEEE

Transactions on Evolutionary Computation, Author's Preprint, 2011: 1-15.
15. Di Pietro A, While L, Barone L. Applying evolutionary algorithms to problems with noisy, time-consuming fitness functions[C]. Proceedings of the 2004 Congress on Evolutionary Computation. Portland, OR, USA: [s.n.], 2004: 1254 – 1261
16. Cantu-Paz E. Adaptive sampling for noisy problems[C]. Proceedings of Genetic and Evolutionary Computation Conf(GECCO'2004). Seattle, WA, USA: Springer, 2004: 947 – 958.
17. Torra V. Hesitant fuzzy sets [J]. International Journal of Intelligent Systems, 25(6):529–539, 2010.
18. Rodríguez R.M, Martínez L, Torra V, Xu Z.S, Herrera F. Hesitant fuzzy sets: State of the art and future directions [J]. International Journal of Intelligent Systems, vol. 29, issue 6, pp. 495-524, 2014.