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Internet Technology and Interaction Design in Intelligent Toy Products with the Internet of Things Architecture

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ABSTRACT

Smart toys are a specific application of modern intelligent technology. Using modern Internet technology to realize the educational function of toys is an important research direction of modern intelligent toys. To combine smart toys with Chinese cultural education and apply virtual experience and interaction design to the teaching process, the virtual experience and interaction design of cultural education in intelligent toy products is studied under the Internet of Things (IoT) architecture. Two interactive genetic algorithm application models are established based on composite fitness allocation strategy (HFAS) and hierarchical fitness allocation strategy. The parameter settings of the composite fitness allocation strategy are analyzed, and the optimal allocation strategy for hybrid fitness is selected. The scheme and the design of intelligent toy products explore the intelligent vehicle design artificial intelligence case applied by the interactive genetic algorithm in the cultural education of intelligent toy products. It can be seen from the algorithm test in the text that for the designer of the smart bowl fern. Through the evolutionary iteration of the feature line, each generation of offspring population can produce five individuals while having less impact on the next generation, can make better individuals, and the design results can better meet customer needs.

Keywords: IoT, Smart Toys, Internet Technology, Virtual Experience, Interaction Design

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1. Introduction

On February 15th, 2015, the Toy Industry Association presented the development trend of toys and games in 2015 at the 112th North American International Toy Fair, including 7 projects: open game time, smart games and cutting-edge high-tech, looking at the toy market. There are many kinds of high-tech toys, among which "smart toys" are most favored by players. These toys are composed of physical and microcomputer components. Through the two-way interaction between users and smart toys, pre-set cognition can be completed. The task of technical and emotional goals is made [1].

Currently, there are many smart toy projects in the world that have achieved great market influence. However, few people combine technology and teaching. From the perspective of researching smart toys, the basic theories and educational rules of intelligent toys in education have not been systematically sorted out by scholars. Therefore, the virtual experience and interaction design of cultural education of intelligent toy products under the framework of IoT is studied. The combination of intelligent toys and education has certain theoretical and practical significance [2]. Literature and typical cases illustrate the development process of smart toys, explore the theoretical basis, teaching mode and innovation potential of its application in education, strive to comprehensively grasp the educational application of smart toys, and stimulate the educational researchers to apply educational toys to intelligent toys.

This paper establishes two application models of interactive genetic algorithm based on combined fitness allocation strategy (HFAS) and fractional fitness allocation strategy. The parameter settings of the combined fitness allocation strategy are analyzed, and the optimal design for intelligent toy products is selected. The artificial intelligence of an intelligent car is taken as an example to discuss the application of interactive genetic algorithm in the cultural education of intelligent toy products. The design results are evaluated using the full replacement and fuzzy evaluation methods.

This paper's research is divided into three parts. The first part introduces the development history, definition and characteristics of smart toys, analyzes the application objects and types of smart toys in education, and analyzes the virtual experience and interaction of smart toys with specific cases. The second part mainly introduces the research status of virtual toys and the virtual design of intelligent toy products under the framework of IoT at home and abroad and provides a theoretical basis for subsequent research. Finally, the adaptive allocation algorithm of the interactive genetic algorithm is typing an intelligent toy product design case that chooses a better solution. The artificial intelligence of an intelligent car is taken as an example to discuss the application of the interactive genetic algorithm in the cultural education of intelligent toy products and tests the algorithm.

2. Related Work

The mid-to-late 1980s was the beginning stage of modern toys in China, and it was only in the 21st century that there was research on smart toys in China. Therefore, the research history of smart toys in China is not long. Wang et al. studied children of different materials. The interactive experience design of toy books was studied. The toy books were summarized from the aspects of material texture, color, sound, shape, smell and taste, shadow, etc., and the influence and function of toy books and material-based interactive experience design on children's growth were expounded [3]. Tao-Tao Li and others believe that China's smart toy market has broad prospects for demand, but lacks independent brands [4]. China has a large population base, the liberalization of the second child policy, and the addition of smart toys. The target audience is no longer limited to children, so the demand for smart toys in the domestic market is huge. Zhan et al. believe that as the world's largest toy producer and Exporting countries, China's well-known toy brands are very few, the lack of independent brands, resulting in China can only exist as a processor role [5]. He et al. concluded through research that the design strategy research helps to bring a more user-friendly user experience [6]. In terms of theoretical research, they also analyzed the concept of smart toys. , characteristics, and explore the impact of smart toys on learning emotions and motivation, at the same time, they have carried out more intelligent toy research projects, and achieved good application results. Amores et al. proposed storytelling to improve children's language skills and imagination, and to form a understanding of the division of social roles in storytelling [7]. Cecchi et al. In the story of the intelligent toy augmented Knights, Castle, children in the storytelling process can enhance the understanding of history, social roles, while cultivating children's ability to cooperate [8]. In technology, on the other hand, Pinheiro and others focused on the technological innovation of smart toys, and used high-tech technologies such as sensor technology, Internet technology, and augmented reality technology to create a large number of creative research and design smart toys, such as Aibo robot dog, Phoebe elves, Sifeo Cubes, smart toy robots [9]. A research work was made on the virtual experience and interaction design of cultural education in intelligent toys under the IoT Foreign scholars Ryan et al. represented this information as a virtual agent in a 3D environment by integrating tracking information from space and the user's head, hands and feet. Each object has a unique look and behavior, such as in a circuit lab. Toy blocks act as switches, batteries and light bulbs. By tracking toys and other everyday objects and integrating them into virtual reality, they created educational and entertaining experiences for children to play and learn more independently [10]. Tseng and others summarized the psychological and physiological characteristics of children, combined with contemporary new materials, proposed the important role of children's toy book interactive experience design in children's growth, providing children with a relaxed and pleasant cognitive atmosphere [11].

In general, based on the research on the virtual experience and interaction design of cultural education in intelligent toy products under the IoT architecture, the number of domestic researches is small and the depth is not enough. This has not received enough attention to the design principles and design standards. The research on the design strategy of teaching purpose is made. Compared with the research on the virtual experience and interaction design of domestic smart toys, foreign countries have far exceeded the domestic development level in both theoretical research and technology development, and have also applied in the field of education.

3. Intelligent toy virtual experience and interaction design method based on the perspective of IoT

3.1 Assignment Algorithm for Adaptive Genetic Algorithms

The composite fitness allocation strategy is that the user first selects a favorite individual and assigns a fitness value of 1.0. The adaptation method of other individuals is based on a fuzzy reasoning method based on the relationship between the selected individual and other individuals. From the user's point of view, the composite fitness allocation strategy is better than the scoring algorithm because the user's task is lighter and the process is faster [12]. However, in practical applications, the user does not necessarily want to reduce the burden, because sometimes the user will face the same situation that the two individuals have the same similarity with the target image, or there is no individual similar to the target. At this time, it is difficult for the user to select only one individual [13]. In these cases, the user would like to select some individuals and give similar degrees of similarity to the target images. Considering the requirements of product conceptual design, in order to create a more natural, in the interactive process, the composite fitness allocation strategy adopted in this paper allows the user to select some individuals and evaluate their phase with the target image. For the degree of degree of satisfaction, that is, the degree of satisfaction, the fitness of all individuals is calculated according to the base distance between the selected individual and other individuals. In addition, the similarity level is reflected in the index calculation of fitness. Simulation, under certain conditions, the fitness of each individual's choice of two individuals is better than that of each individual [14]. This particular condition is that each individual. The level of similarity with the target individual is not very large, and the degree of similarity between the individual and the two target individuals is relatively small. This compound strategy helps to achieve a more natural interaction process under actual operation. Both correspond to a point in space, which consists of various parameters describing the individual image. This space is called the parameter space [15]. The coordinates of the individual i are expressed as follows:

$$P_i = \left(p_{i1}, p_{i2}, p_{i3}, \ldots, p_{in}\right), p_{\min} \le p_{ij} \le p_{\max} \quad (1)$$

Among them, $p_{\min}$ and $p_{\max}$ refer to the maximum and minimum values of p_{ij}, n is the number of parameters or the dimension of space. The formula for calculating the distance between individuals i and j in the parameter space is as follows:

$$dis\tan ce = \sqrt{\sum_{k=1}^{n} \left(p_{ik} - p_{jk}\right)^2} \quad (2)$$

Since each parameter has a different degree of influence on the similarity between individuals, the distance relationship described in equation (2) can be further expressed as a weighted form as follows:

$$dis\tan ce = \sqrt{\sum_{k=1}^{n} w_k \left(p_{ik} - p_{jk}\right)^2} \quad (3)$$

w_k is the weight of the kth parameter. In this study, the weighted search method is not simulated, so the distance will be calculated using the unweighted method using the formula (1). In the compound allocation strategy, the user can select an arbitrary number of individuals, and assigns a level according to the degree of similarity between each selected individual and the target. The fitness of the selected individual is specified as a maximum value of 1.0, and the fitness of other individuals is based on the selected individual and other individuals. The distance in the parameter space is calculated. After selecting an individual, the fitness of the *i-th* individual f_i is calculated by the following formula;

$$f_i = \left(\frac{d_{\max} - d_{i-s}}{d_{\max}}\right)^a \quad (4)$$

Where $d_{\max}$ is the maximum value of the distance in the parameter space, and *a* is a constant. When the fitness is linearly proportional to d_{i-s}, the constant a takes a value of 1.0. In order to reflect the similarity level *g* when calculating the fitness, an exponential method is usually used. The equation is as follows:

$$f_i = \left(\frac{d_{\max} - d_{i-s}}{d_{\max}}\right)^{3.0g} \quad (5)$$

The similarity level *g* reflects the degree of similarity between the selected individual and the target image, usually between 0.0 and 1.0. If the user selects two individuals *A and B*, their similarity levels are *g*(*A*) and *g*(*B*), a certain body *i* therefore has two different fitness degrees, *fi*(A) and *fi*(*B*) are calculated by the formula (6). Then the fitness of the individual *i* is defined by the fitness with the weighted average of similar levels. The following formula is calculated:

$$f_i(Com) = \frac{g(A)f_i(A) + g(B)f_i(B)}{g(A) + g(B)} \tag{6}$$

Finally, the standard values calculated by $f_i(Com)$ and $f_{\max}(Com)$ are used as the fitness values of the individual i.

$$f = \frac{f_i(Com)}{f_{\max}(Com)} \tag{7}$$

3.2 Interactive Genetic Algorithm Genetic Coding for Intelligent Toy Product Design

The interactive genetic algorithm is simple in form and has good global search ability, and the control parameters of the interactive genetic algorithm have an important influence on the performance of the interactive genetic algorithm. How to set the control parameters of the effective interactive genetic algorithm is to decide the interaction. The key to the success of genetic computing is found. There are three main interactive genetic algorithm control parameters, namely population size, crossover probability and mutation probability. For population size (n): population size refers to the number of all individuals in the search population. The scale directly affects the computational efficiency of the interactive genetic algorithm and the quality of the solution obtained. The population size is too small, prone to premature convergence, and falls into local optimization; if the population size is too large, the calculation amount will increase too much, and the calculation time is too long. In this study, the population size was chosen to be 8 and the search algebra was 10. Each search involved 88 individuals. For the crossover probability (P_c): the crossover probability determines the number of individuals who cross-operate in each generation, for example when the population size is n=100, $P_c = 0.8$ At the time, there will be 80 individuals performing cross operations. The crossover probability affects the individual's Probability and mutation probability. In this study, $P_c = 0.6$. For the mutation probability (P_m): the mutation probability determines the number of times each gene in each population is mutated. If the individual coding length is L, then each individual has an average $P_c \times L$ is mutated. The mutation operation is beneficial to maintain the diversity of the population. The mutation probability affects the performance of the mutation operation. The P_m is too large to make the genetic algorithm a random search. The is too small and will make the allele lacking in the genetic algorithm population, which is hard to recover.

Everyone's body can be described by about 30,000 genes expressed in four letters A, C, G and T, or only a series of 0 and 1 if you want to use binary expression. Two people are regardless of the table. The difference in type (i.e, appearance) is significant, and their differences only come from a small percentage of genetic differences. For mechanical products, genes can also be used to express their appearance characteristics. Figure 1 shows the gene expression of the packaging line product. Genes are used to represent parts, and chromosomes represent components. Through this way of correlating genes with product features, products can be clearly layered.

In genetic algorithms, there are two kinds of data conversion processes, namely, encoding operations and decoding operations. The encoding operation is a conversion from phenotype to genotype, that is, the product design is transformed into a chromosome or a gene in the genetic space. The conversion from genotype to phenotype, the opposite of the decoding operation, binary coding is a commonly used coding form in genetic algorithms. If not specified in the following discussion, it will be interpreted by binary coding, packaging machinery products. The appearance feature can be regarded as the phenotype of the interactive genetic algorithm. After determining the value interval and precision of each parameter, the features of each module can be encoded, that is, the characteristics of each module correspond to a bit string. The length depends on the length of the interval and the complexity of the module's characteristics, combining a series of bits from all the module features (the solution to the problem) to form a chromosomically encoded string, which is mapped to the binary by coding, the solution to the problem (phenotype) Chromosomal coding string (genotype).

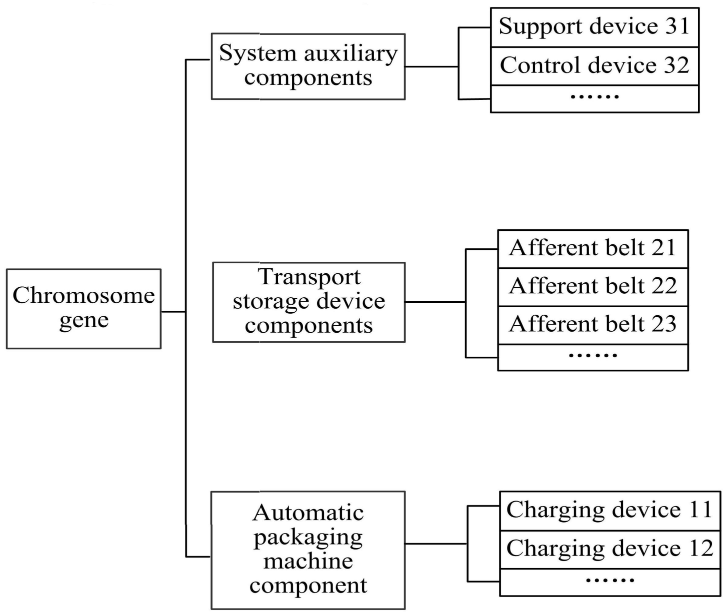

Figure 1. Gene expression in packaging line products

4. Experimental Design and Analysis

4.1 Test Conditions and Parameters

Through the evolutionary iteration of the feature line, it is guided by the evolutionary route of the designer's fitness evaluation. The most adaptive individual in the evolution process is the most ideal feature line scheme in the generation. The stylist firstly carries out the five individuals in the initial population. In the evaluation of fitness, each generation evolves to contain five individuals. Each individual stylist gives the corresponding fitness. The termination of the algorithm is determined by the stylist until the stylist is satisfied with the evolution result. The stylists in the 2nd, 4th, 6th and 8th generations respectively gave the individuals with the highest fitness. The figure 2 shows the calculation of the detection operator for a two-variable multi-objective optimization problem. The non-dominated solution set at the restart of the problem and the two new individuals generated by the probe operator can be seen that one of the two new individuals is generated in a region where the non-dominated solution is relatively densely distributed. The other is produced in a region where the non-dominated solution is relatively sparse.

4.2 Algorithm Test

According to the foregoing description, the design variables of single-objective optimization, design goals and constraints have been determined and an interactive mini-genetic algorithm has been adopted. The following is given according to the above description. The first is the initial population of the algorithm. The stylist gives the

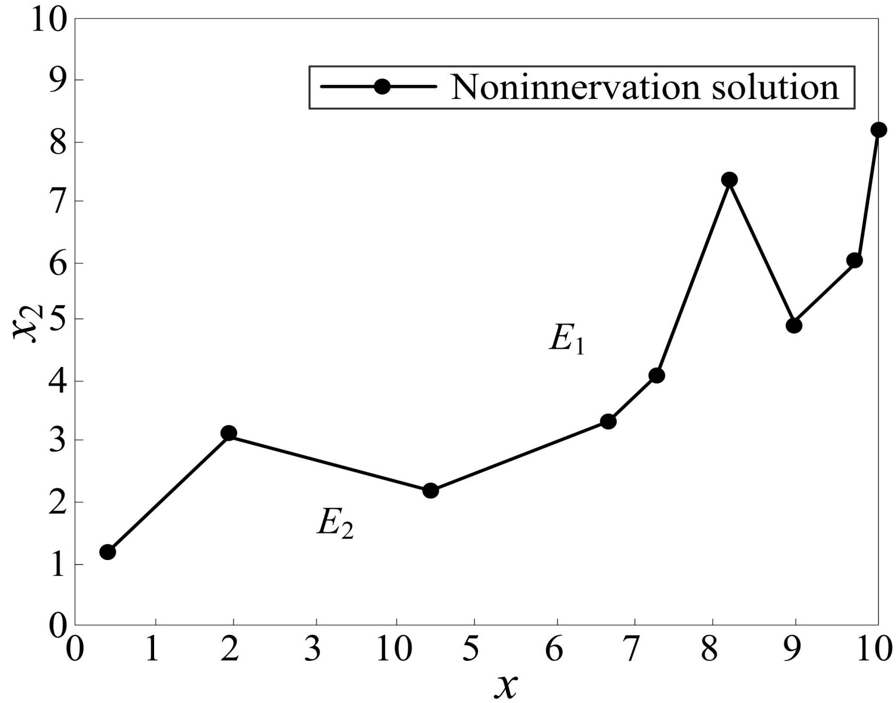

Figure 2. The calculation of the detection operator for a two variable multi-objective optimization problem

initial population in this example. According to the previous introduction, the algorithm has 23 design variables, and each generation has 5 individuals, thus obtaining the following initial populations, as shown in Table 1. The algorithm uses the binary coding mechanism to read the population after reading the initial population. The decimal form is converted to binary. After reading the initial population, each individual is evaluated. The stylist gives different evaluations according to the aesthetics, aerodynamics and expectations of each toy.

According to the expectations of the experts, the stylist's specific scores on the aesthetics of the five individuals in the initial population are shown in Table 2. The scores range from 0 to 9, as shown in Table 2, the experts have modeled 05 toys. There is a higher evaluation, by giving higher scores, it is expected that the resulting offspring individuals will inherit more of the individual's genes. The stylist's aerodynamic specific scores for the five individuals in the initial population are shown in Table 3. The scores are also the same. Between 0 and 9, experts believe that the 05 toy models perform best in aerodynamics, so they give higher scores, and hope that the resulting offspring population will inherit more of the individual's genes.

Case name	The 94 model year	The 98 model year	The 99 model year	The 02 model year	The 05 model year
Score	3	4	4.5	7.5	5

Table 1. Initial aesthetic value of sample case

Case name	The 94 model year	The 98 model year	The 99 model year	The 02 model year	The 05 model year
Score	5	4.5	5.5	6	7

Table 2. Initial aerodynamic value of sample case

Case name	The 94 model year	The 98 model year	The 99 model year	The 02 model year	The 05 model year
Score	4.5	4.75	5.2	6.8	6

Table 3. Initial average value of sample case

Through the evolutionary iteration of the feature line and the evolutionary route of the designer's fitness evaluation, five individuals can be generated in each generation of the offspring population. Individuals who conform to the constraint mechanism are artificially assigned fitness, and do not conform to the individual of the constraint mechanism. Give the individual a small degree of fitness, so that the individual's impact on the next generation is relatively small, which is conducive to producing better individuals.

The following are the non-dominated solutions generated by the algorithm. The first generation produces a non-dominated solution (see Figure 3). After the second generation, there are three non-dominated solutions. The algorithm is performed for 10 generations, and finally the non-dominated solution is obtained. The number of the five individuals is 5. In the five individuals generated, the algorithm selects a reasonable individual as the non-dominated solution. After the algorithm evolves to a certain number of algebras, the stylist can terminate the evolution and select the optimal individual from the non-dominated solution set. Selecting the optimal individual for each generation also requires the stylist to evaluate each solution. The evaluation can be weighted by the two fitness assigned to the individual, and the highest weighted is the optimal individual. The genetic algorithm runs to the tenth. In the generation, the five non-dominated solutions are obtained. The final optimal individual can be selected from the five. In the public $f = \alpha_1 f_1 + \alpha_2 f_2$, the corresponding weights are given to get an individual that best meets the requirements of the stylist. For example, setting $\alpha_1 = 0.4$, $\alpha_2 = 0.6$ can get the penultimate solution as the optimal solution (See Figure 4).

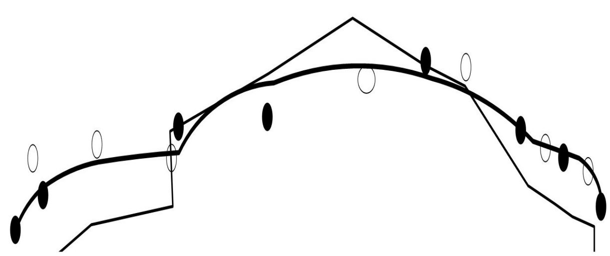

Figure 3. The score of aerodynamics is 5ÿand the aesthetic score is 6

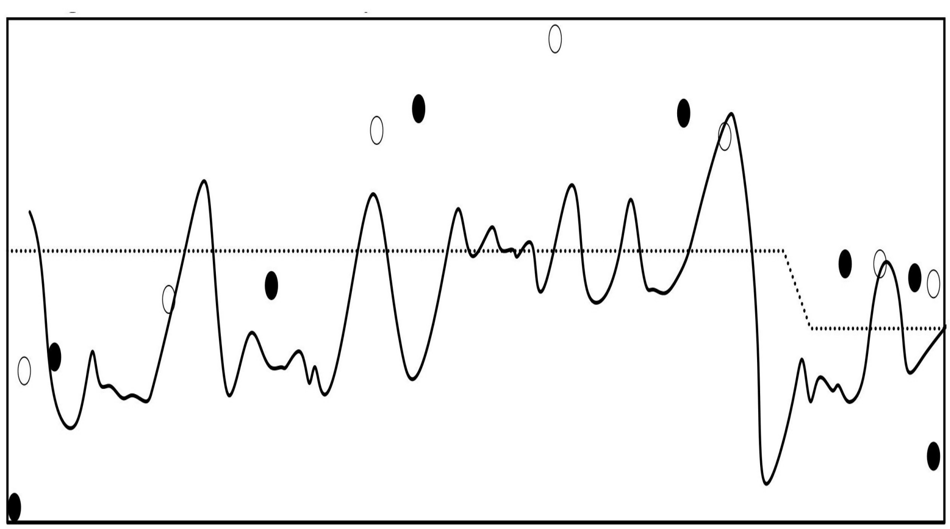

Figure 4. The optimal solution of figure 3.271 a=0.4ÿ2 a=0.6

Computer-aided design platform is used, using computer-aided design technology, including Skipup, AutoCAD, ATD and other auxiliary software as technical support. In the secondary development, VC++ combined with AutoCAD object-oriented technology is used to introduce algorithms to form a digital design environment. The design of the virtual toy virtual experience and interaction design is layered output. The layered management of the graphics is to deal with the different use of different graphics. The computer simulation of the whole design is shown in Figure 5, Figure 6 and Figure 7.

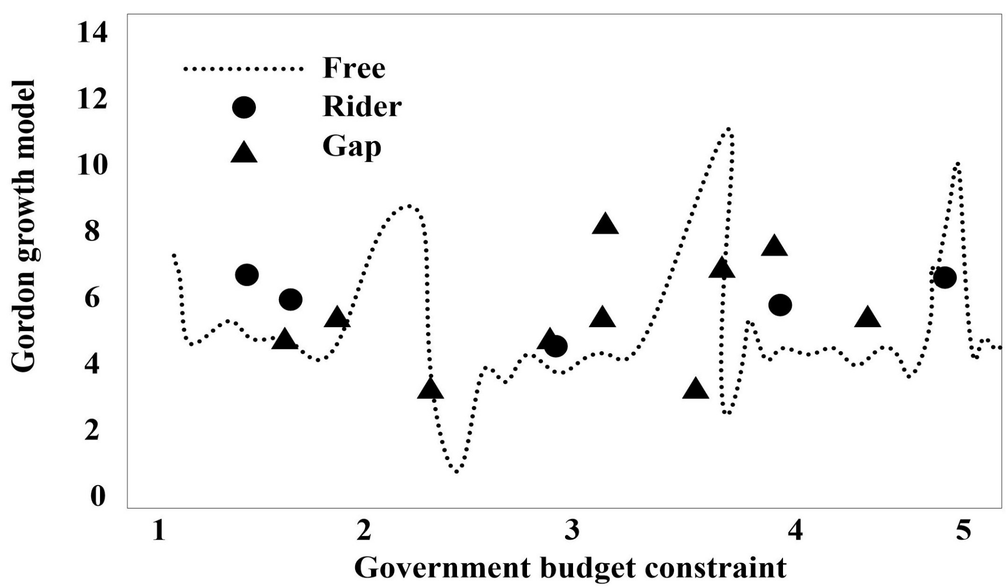

Figure 5. planning land (area 160 acres)

In the design process, the parameters of the algorithm part of this paper change as follows:

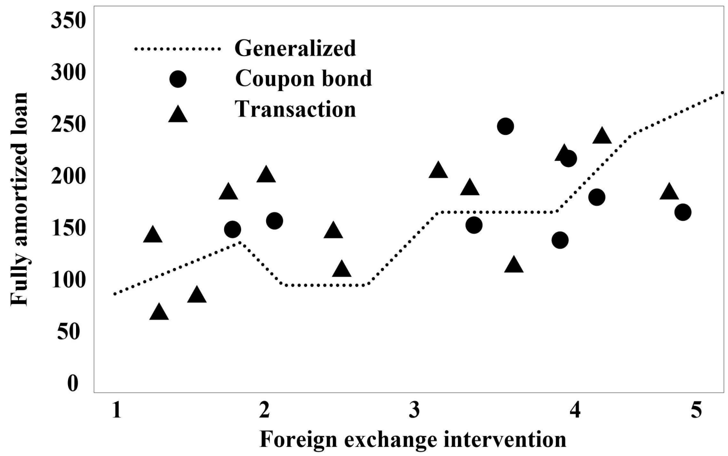

Figure 6. The parametric design vision schematic diagram

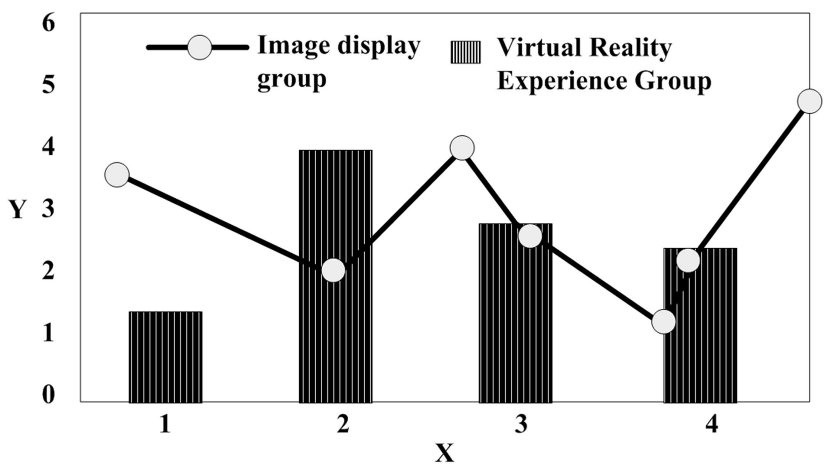

Figure 7. Respondents can understand design chart

Interaction design is the design field that defines and designs the behavior of artificial systems. It defines the content and structure of communication between two or more interacting individuals, so that they can cooperate with each other to achieve a certain purpose. Interaction design strives to create and establish a meaningful relationship between people and products and services, centered on "embedding information technology in a material world full of social complexity". The goal of interactive system design can be analyzed from the two levels of "availability" and "user experience", focusing on the user-oriented user needs. This paper starts from the origin, development status and design principle of interaction design ideas, and draws on existing theories and methods. Successful experience, researched the application of virtual experience and interaction design method in the design of intelligent toy car, and introduced the genetic and evolutionary laws of biology into the design and brand design of intelligent toy cars. Interactive evolutionary algorithm is used to design the intelligent toy car styling feature line based on the designer's desired image, combined with the characteristics of intelligent toy car styling feature line gene expression and the realization of the example-based intelligent toy car styling interaction design system, feature line modeling. The evolutionary algorithm uses a micro-genetic algorithm.

5. Conclusions

The intelligent toy car model is taken as the design object, analyzes the virtual experience and interaction design of cultural education in IoT smart toys. Based on the application of intelligent interactive genetic algorithm in the design of intelligent toy car model, through the shape characteristics and development of smart toy car, the research of trend summarizes the product design. Design points and characteristics are analyzed, and an intelligent vehicle modeling module partitioning method is proposed based on interactive genetic algorithm. The application of interactive genetic algorithm in intelligent toy car interaction design is found and the process is studied to construct an application model of interactive genetic algorithm in the conceptual design of smart toy cars. On this basis, the adaptive allocation strategies, scoring strategies and combined fitness allocation strategies of two interactive genetic algorithms are further proposed and verified in specific design cases. By constructing qualitative and quantitative design evaluation systems, the design of interactive genetic algorithm conceptual design examples is evaluated from different angles, and the interactive genetic algorithm is applied to the conceptual design of intelligent vehicle modeling. Finally, Matlab and CATIA software are used to realize the interaction. The application of genetic algorithm in 3D design platform is made. The results show that the interactive genetic algorithm can assist product concept design and generate optimized design scheme compared with the two-dimensional design scheme of previous genetic algorithm in mobile phone modeling and fashion design. The research has a better application in the research of 3D model aided design. However, the research in this paper still has certain deficiencies. For example, the algorithm proposed in this paper can only design simple models, simple interaction, more complex models or more interesting interactions need to be developed in future research.

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