Cognitive Mechanisms and Optimization Strategies in Interactive Evolutionary Design Based on Cognitive Load Theory

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Abstract. The interactive evolutionary design (IED) approach is a human-centered design method with the design domain, which requires users to evaluate their overall satisfaction with evolutionary individuals. However, due to repeated and continuous interactions, users experience varying degrees of physical and psychological fatigue. How to alleviate user fatigue has become an important research topic. Some researchers focus on algorithm mechanisms, evaluation methods, and interface design improvements, whereas the relationship between user cognitive characteristics and interaction design has been less studied. This paper analyzed users' cognitive mechanisms and proposed optimization strategies for the IED based on cognitive load theory. First, user cognitive activities were identified during different stages, and the type of cognitive load was determined in each cognitive task. Second, combined with cognitive load effects, we proposed the optimization strategies for intrinsic, extraneous, and germane cognitive loads. Third, we adopted two existing algorithms and developed corresponding design systems to discuss the effectiveness of the proposed strategies. To achieve this, ten subjects were invited to operate systems, with experimental data recorded and cognitive load levels measured. The main findings from this paper highlighted that the proposed strategies effectively reduce the extraneous cognitive load and improve the efficiency of germane cognitive load.

Keywords: Cognitive load theory · Interactive evolutionary design · Human-computer interaction

1 Introduction

The interactive evolutionary design (IED) is an intelligent design approach based on the interactive genetic algorithm (IGA). By introducing user evaluation as individual fitness to guide population evolution, the IED has been widely utilized in various design scenarios, such as shoe and fashion design [1–3], industrial product design [4–7], pattern design [8–10], character design [11, 12], etc. Due to the limitations of human cognitive abilities, repeated interactions between users and systems lead to varying degrees of users' physical and psychological fatigue. Thus, user fatigue has become an important factor limiting the practical problem-solving ability of the IED. To alleviate this issue, many

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researchers have proposed various improvement methods, such as introducing surrogate models to replace user evaluation tasks [6, 13], improving the interactive evaluation mechanism to simplify users' operations [14], adopting proper fitness representations to accurately capture user preferences [15], etc. These studies emphasized the influence of user cognitive process on algorithm performance, but few have systematically explored the user cognitive characteristics in the IED.

Based on cognitive load theory, this paper systematically analyzed the cognitive process of users in the IED. First, the information entities and specific tasks were deconstructed during the user cognition process, and the types and causes of cognitive load were clarified in different tasks. Second, corresponding improvement strategies were proposed based on cognitive load effects. Third, to verify the effectiveness of the proposed strategies, we selected the painting design for the road roller as a case. Two existing improved algorithms were selected based on the strategies, and corresponding IED systems were developed. Then, ten subjects were invited to perform design experiments, with data recorded, analyzed, and discussed.

There are three main contributions in this paper, which are: (1) A systematic study on the user cognitive process in the IED is conducted based on the cognitive load theory. This will help to explain the causes of user fatigue from the cognitive aspect; (2) the proposed corresponding improvement strategies provide new ideas for the design of specific algorithms; (3) We contribute to the development of IED system by exploring the implementation path of the proposed strategies for specific problems. It provides a reference for improving design efficiency, reducing design costs, and realizing design intelligence.

The remaining sections of this paper proceed as follows: Sect. 2 reviews the existing research on the IED and cognitive load theory, and summarizes the problems. Section 3 elaborates on the user's cognitive process, and the specific improvement strategies. Section 4 is the theoretical verification and case study. Section 5 presents the conclusions, limitations, and future research work.

2 Related Work

2.1 Interactive Evolutionary Design

The IED is a human-machine collaborative design method based on the IGA. The IGA was proposed by Dawkins [16] in 1986 and is considered to be a genetic algorithm that effectively solves the implicit objective optimization problem. In the traditional interactive genetic algorithm (TIGA), users need to evaluate the population schemes generated by the algorithm based on their preferences. Then, the algorithm utilizes the user evaluation as individual fitness to perform the selection, crossover, and mutation in sequence, and generates the next generation population.

However, the various operations increase the cognitive burden of users at different evolutionary stages in the real case, due to the limited cognitive ability of users. These stages are: (1) The early stage of evolutionary design, which is difficult for users to establish a clear relationship between design objectives and scheme characteristics. Users need to reflect and confirm the schemes repeatedly before they build a mapping relationship between the abstract objectives and the specific characteristics. This cognition ambiguity leads to evaluation noise, which interferes with the individual optimization of the IGA and reduces the algorithm efficiency. Meanwhile, repeated reflection and confirmation increase the user's cognitive load and reduces the user's cognitive efficiency. (2) The middle of evolutionary design. As the number of individuals evaluated and the duration increase, the user's cognitive load increases. Users face physical and psychological fatigue, which leads to evaluation errors. Therefore, how to reduce the cognitive load and to improve cognitive efficiency is the key to alleviating user evaluation fatigue and ensuring the feasibility of the IED in practical applications.

Aiming at the user cognitive activities in the early stage, Yang *et al.* [17] constructed a cognitive noise model to mitigate the impact of the inaccurate user evaluation. Zeng *et al.* [18] proposed a "Text-Image-Symbol" mapping strategy, which requires users to select a text description (emotional adjective) that meets the design objectives. Then, based on the selected text description the system provides stimulus pictures to help users to specify the characteristic representation of the design objective. At present, there are few studies of research on user cognition at this stage. Existing studies mainly focus on the reduction of evaluation noise caused by user cognition ambiguity, with less consideration to improving user cognitive efficiency.

For the cognitive problems in the middle stage, existing studies pay attention to improving the fitness representation, updating the evaluation mechanism, and constructing the surrogate model:

(1) Improvements for fitness representation. In the TIGA, users need to choose a number as individual fitness based on their preferences. This fitness representation method requires users to accurately distinguish the differences among population schemes, resulting in an additional psychological burden. In response to this problem, Ohsaki *et al.* [19] used discrete fitness to divide the assignment interval into fewer levels, such as the utilization of a three-points or five-points scale for individual evaluation. Besides, the relationships were also studied between the number of levels and algorithm convergence. Gong *et al.* [20] proposed a fitness representation method based on interval numbers. In this method, users need to assign two numbers as the upper and lower limits of the interval fitness. This method reduces the accuracy of user evaluation and the user's psychological burden, but complicates the evaluation operation itself. Dou *et al.* [21] improved the method of literature [20] and proposed an interval fitness based on user hesitancy. Users only assign a number as the center of the individual interval fitness. The algorithm estimates the width of the interval fitness based on the evaluation time. Gong *et al.* [22] adopted fuzzy numbers expressed by the Gaussian membership function to represent individual fitness. This method requires users to select a number as the center value of the fuzzy fitness. Then, a modal word (such as "about", "close", "very close", etc.) needs to be selected as the width of the fuzzy fitness.

(2) Improvements to the evaluation mechanism. Because user preferences are difficult to quantify, the individual evaluation that needs to assign a specific number increases the psychological burden on users. Therefore, researchers have studied non-assigned evaluation methods. Cheng *et al.* [23] calculated individual fitness by extracting user eye movement information. Takenouchi *et al.* [11] proposed an interactive genetic algorithm based on group user eye movement information. The

proposed algorithm uses the B5T007001 device to collect the eye movement information of the user group, combined with the Paired Comparison Method (PC), to infer the preferences of the user group, and output design schemes that satisfy the group.

(3) Construction of the surrogate model. These methods take individual genotypes as the input and the user evaluation results as the output to build a machine learning model to simulate user preferences and predict individual fitness. Lv *et al.* [13] presented an agent model of the user cognition based on the Back Propagation Neural Network (BPNN) to predict individual fitness and reduce user cognitive burden. [6] introduced BPNN to replace user evaluation and alleviate user fatigue.

The first category of research aims to reduce the accuracy of evaluation operations to mitigate the user's psychological load. Meanwhile, the fitness representation is designed to reflect the ambiguity and gradualness of the user's cognition. But such methods still require user assignment operations, which increases user' cognitive loads. The second category of research simplifies the evaluation operation, and users do not need to assign a specific number. The cognitive load is reduced during the evaluation. The disadvantage of these methods is that the evaluation accuracy is low, accompanied by large noise. And it is difficult to determine the general relationships between eye movement/EEG data and user preferences. The third category directly reduces the number of individuals evaluated by users. However, an accurate agent relies on a large amount of user evaluation data. The evaluation data of users are limited, and the evaluation results usually contain noise in the IGA. It is difficult for the agent to accurately fit the user preference characteristics. In short, few of the above studies can balance algorithm optimization efficiency and user cognitive load. Furthermore, the aforementioned studies seldom consider user cognitive characteristics and changes throughout the evolutionary process.

Therefore, this paper attempts to systematically study the cognitive mechanisms of users in the IED and explore optimization strategies that reduce cognitive load and improve cognitive efficiency, ensuring effectiveness in solving practical design problems.

2.2 Cognitive Load Theory

Cognitive load theory (CLT), was proposed by Sweller in 1988 [24]. CLT points out that the human cognitive structure consists of limited working memory and unlimited long-term memory. The human cognitive process is considered to be a process of consuming cognitive resources. Any learning and problem-solving activities are accompanied by cognitive processing behaviors. CLT aims to achieve a reasonable allocation of cognitive resources in the process of task completion. It focuses on different types of cognitive load in the instruction process, and guides the design of instructional content and material presentation. Because human cognition is closely related to many fields and applications, CLT has attracted the attention of various disciplines.

CLT divides the human cognitive load into the intrinsic cognitive load, the extraneous cognitive load, and the germane cognitive load [25]. The accumulation of three types of cognitive load equals the total cognitive load level. The intrinsic cognitive load is the cognitive load generated in the process of processing instructional materials in human working memory. It is mainly related to the complexity of the materials and tasks. Wang *et al.* [26] believed that the internal cognitive load is not easy to alleviate through external intervention. The extraneous cognitive load refers to the cognitive load caused by unreasonable instructional design or material presentation. It occupies the learner's working memory resources and leads to insufficient resources for task completion. The germane cognitive load, known as the effective cognitive load, is the cognitive load that occurs at the stage of deep processing of instructional information. It is relevant to schema construction and automation. Moderate germane cognitive load facilitates task completion and improves learning efficiency.

As mentioned in Sect. 2.1, user cognition issues reduce the effectiveness of the IED in practical applications. From the perspective of CLT, the user evaluation task in the IED is essentially a task of perceiving and identifying their preferences and characteristics of population schemes. The design of the IED systems is a design process of the instructional tasks. How to systematically inquire about the cognitive mechanisms and optimize strategies in the IED based on CLT, is worthy of further research.

3 Cognitive Mechanisms and Optimization Strategies

3.1 Information Entities and Specific Tasks in the IED

In the IED, the different cognitive processes involve different information and tasks. These include not only the presented information and the assigned tasks in the system, but also the implicit information and tasks that exist in the user's consciousness. Combined with the thinking process of designers in traditional design tasks, the information entities and specific tasks are represented in the IED, as shown in Fig. 1.

In the traditional product form design, experienced designers' thinking has typical linear characteristics [27]. Designers firstly clarify design objectives based on enterprise or user requirements (mostly expressed in descriptive text, such as adjectives, paragraphs, etc.). Then, based on personal experience and preferences, designers search for reference cases (mostly expressed in pictures or videos) that match the design objectives. Through the consideration and analysis of reference cases, the specific morphological characteristics are extracted for the expression of objective images. And the mapping relationship is constructed between abstract design objectives and tangible characteristics. Then, designers modify and integrate characteristics to sketch. Finally, it is necessary to invite design experts, enterprise representatives, and users to conduct a comprehensive evaluation of the sketch schemes. Based on the evaluation results, designers revise and iterate the sketch schemes until the design objectives are met. Therefore, in traditional design activities, the information entities that need to deal with are design objectives, reference cases, morphological characteristics, and sketch schemes. The specific tasks are respectively the search for reference cases, the extraction of characteristics, the modification and integration of characteristics, and the evaluation and iteration.

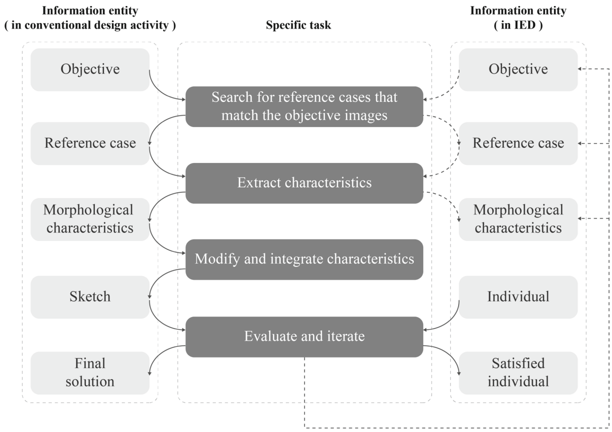

Fig. 1. Information entities and specific tasks in conventional design activities and that in the IED

In the IED, the explicit information entities are the population individuals (schemes) generated by the system, and the specific task is the continuous evaluation of population individuals. Given the cognitive activities in product form design, users also perform the reference search and the characteristic extraction. But these information entities and specific tasks are tacit in the user cognition, and occur in the user's working memory and long-term memory. Users need to search for references related to the design objectives from long-term memory. Based on these reference cases, morphological characteristics, which help express objective images, are refined in working memory. For inexperienced users, the number of relevant references is limited in their long-term memory. The ability to extract characteristics is also limited. It leads to low cognitive efficiency in the early stage of the IED. Users gradually clarify the mapping relationship between design objectives and individual characteristics through multiple evaluations and self-reflection. Thus, the information entities that need to be processed by users are divided into two categories: the first category is explicit and visible in the IED system, such as population individuals; the second category is implicit and invisible, which stored in the user's long-term memory, such as design objectives, reference cases, and morphological characteristics. The specific tasks also include two categories: the first category is the evaluation of population individuals; the second category is the search of reference cases, and the extraction of individual characteristics (occurring in the user's working memory).

3.2 Types and Causes of Cognitive Load in the IED

The relationship between the IED and the user cognition is shown in three stages, as shown in Fig. 2. Phase 1 is the association construction between design objectives and individual characteristics. Phase 2 is the user evaluation. And Phase 3 is the algorithm design. The first two phases are directly related to the user's cognitive process, and the third phase is related to the task difficulty of the IED.

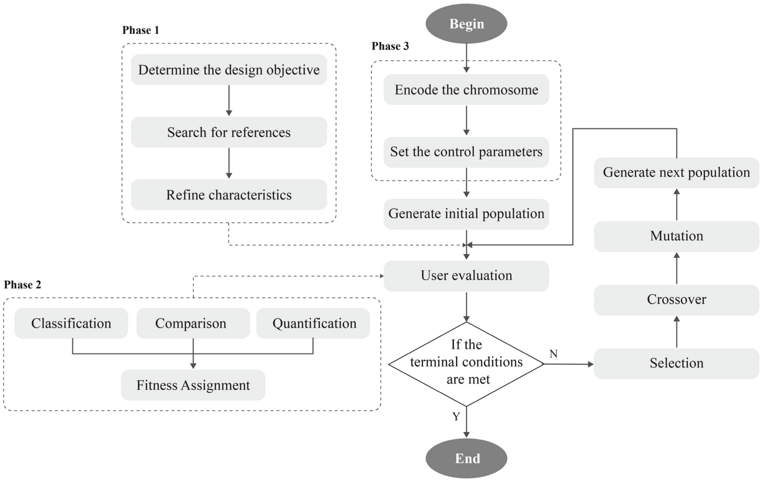

Fig. 2. Three phases involving cognitive load in IED

In TIED, users are not required to perform the tasks of Phase 1. However, as Sect. 3.1, associative cognitive processes are necessary for design activities. They occur spontaneously in user's working and long-term memory, and vary among users: when the design problem to be solved is in the domain familiar to the user, the user's long-term memory stores rich reference cases and clear individual characteristic extraction paths (schemas). This process occupies few cognitive resources; when the problem belongs to their unfamiliar domain, the user's long-term memory lacks relevant references. The schema for extracting individual characteristics is also insufficient. It is difficult to construct the mapping relationship between design objectives and individual characteristics in a short period. This increases the user's cognitive load, and leads to the user's cognitive fatigue for the evolutionary population, making evaluation results contain noise. According to the three types of cognitive load, the cognitive load in Phase 1 is related to the number of references and the schema of characteristic extraction in the user's long-term memory. And it is also related to the information processing ability of the working memory. As shown in Fig. 3, it is obvious that the cognitive load involved in Phase 1 belongs to the germane cognitive load.

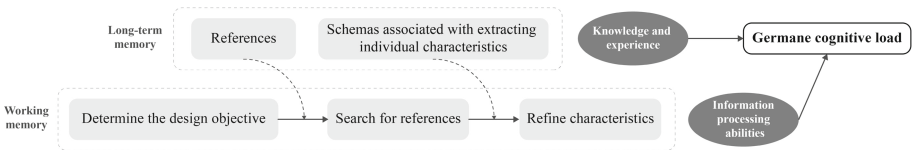

Fig. 3. The type of cognitive load in Phase 1

Phase 2 is the user evaluation stage. It involves the primary operation process of users in the IED. The tasks in Phase 2 require users to perform three cognitive activities in working memory, namely classification, comparison and quantification.

Classification refers to the division of individual categories based on cognitive similarity. The cognitive similarity is usually based on two dimensions: emotional and rational. The emotional dimension is derived from preference and intuition, guided by subjective factors. The rational dimension is based on objective factors such as shape, color, structure, etc. For example, products with a similar emotion (such as “modern”) may have significant differences in the rational dimension (such as the product shape).

Comparison refers to the user’s judgment on the pros and cons of individuals based on design objectives and preferences. Watanabe *et al.* [28] pointed out that it is difficult for users to directly assign a quantified fitness value to evaluate an individual. Users need to compare other individuals to determine their preferences for the individual. Through the comparison, users gradually understand the relationship between the individuals of the current generation, which is beneficial to the construction of the mapping relationship between design objectives and individual characteristics. Meanwhile, it also ensures the accuracy of individual evaluation.

Quantification refers to the quantification process of user preferences. Users usually first select the individuals with a deep impression, and assign an absolute number as the individual fitness based on design objectives and preferences. Through the classification and comparison, the relationship between individuals is clarified. Then, based on the fitness of the individuals evaluated, the specific fitness values of other individuals are determined.

For users who lack experience in design evaluation, the above three cognitive activities are usually incomplete and disordered. The types and causes of cognitive load involved in this stage are shown in Fig. 4. Usually, the presentation of population individuals is random in the IED. It is difficult for users to classify individuals. Users need to consume additional working memory resources to complete individual classification. Besides, in the TIED, users need to evaluate the individuals one by one, which is not conducive to comparing as a whole. The random presentation of individuals and the inappropriate evaluation mechanisms are a matter of presentation method and procedure design. On the other hand, preference quantification also involves the mapping relationship between objectives and characteristics, similar to Phase 1. Therefore, this phase involves both extraneous and germane cognitive load.

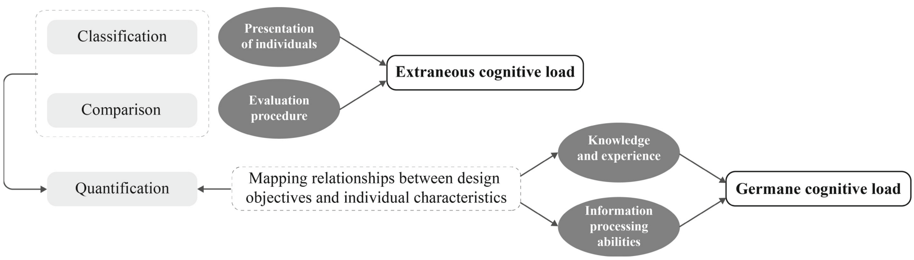

Fig. 4. The type of cognitive load in Phase 2

Phase 3 is the algorithm design stage. In the IED, chromosome encoding and evolution parameter settings determine the complexity of the overall evolutionary design. Generally, the number of chromosome bits is related to the objective complexity of the design task. The larger the number of chromosome bits, the more solutions the algorithm can generate, and the search process of the user's satisfactory solution set becomes more complicated. The crossover rate and mutation rate settings determine the convergence speed of the algorithm. The greater the crossover rate, the more frequent the recombination of individual alleles. The greater the mutation rate, the more frequent the change of individual alleles. The increase of both accelerates the individual change in the population. The increase of both also improves the algorithm's ability to search for unknown domains. Therefore, the crossover and mutation rate setting needs to consider a balance between convergence and unknown domain search. In short, the algorithm design in Phase 3 is directly related to the task complexity of the IED, and is usually completed by designers and developers. According to the cognitive load classification in Sect. 2.2, the cognitive load involved in this stage belongs to the intrinsic cognitive load, as shown in Fig. 5.

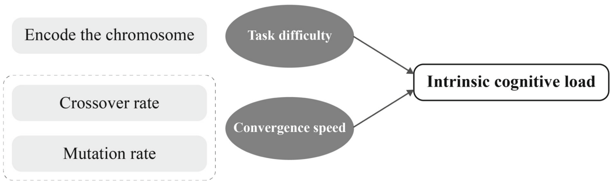

Fig. 5. The type of cognitive load in Phase 3

3.3 Improvement Strategies Based on Cognitive Load Effects

How to reduce the cognitive load level of taskers in the task completion process is the focus of CLT. Since the intrinsic cognitive load is related to the complexity of the task itself, it is usually not influenced by the task design. Thus, there are more studies on reducing the extraneous cognitive load and moderately increasing the germane cognitive load [29].

Researchers have concluded twelve main cognitive load effects based on theoretical research and practical experience, including the goal-free effect, the worked example effect, the completion problem effect, the split-attention effect, the modality effect, the redundancy effect, the expertise reversal effect, the guidance fading effect, the imagination effect, the element interactivity effect, the isolated interacting elements effect, and the variability effect. See [30] for a detailed description of each effect.

According to the cognitive load effects, improvement strategies are presented based on the three types of cognitive load described in Sect. 3.1 (as shown in Fig. 6).

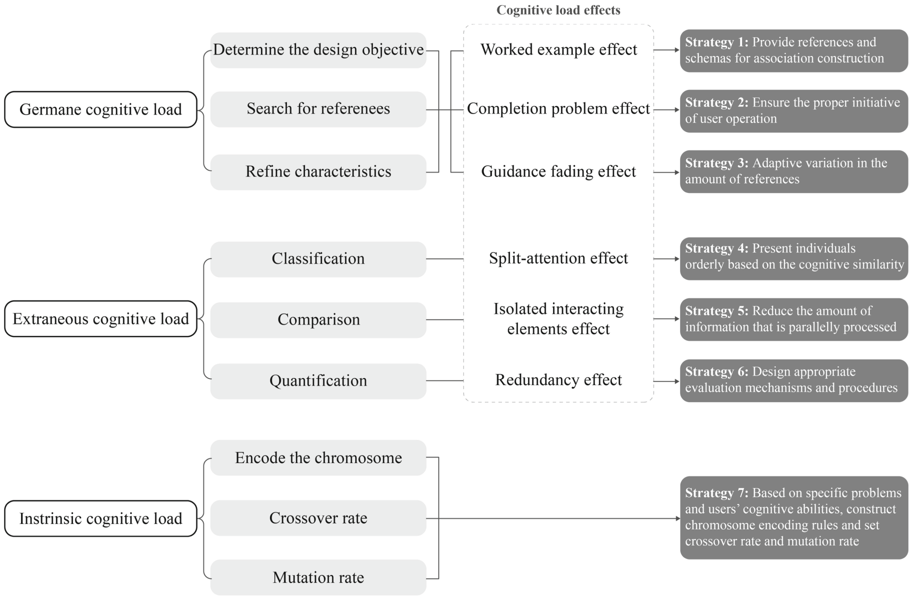

Fig. 6. Improvement strategies of IED based on cognitive load effects

The germane cognitive load in the IED is primarily related to the associative construction between design objectives and individual characteristics. In TIED, the processing of information entities and specific tasks completely depends on the user's working and long-term memory. Therefore, the cognitive load effects related to the example are combined to provide users with references consistent with the design objective. At the same time, the explicit schema construction also needs to be considered. Accordingly, the following strategies are proposed:

Strategy 1: Combined with the worked example effect, materialized references and step-by-step association construction schemas should be integrated into the IED system to facilitate the association between design objectives and individual characteristics in the early stage of evolutionary design.

Strategy 2: Combined with the completion problem effect, an interactive association construction procedure that promotes the user's enthusiasm and participation should be designed to mobilize the user's reflection.

Strategy 3: Combined with the guidance fading effect, the number of materialized references should be adaptively adjusted according to algorithm optimization to prevent redundant references from occupying additional cognitive resources.

For the extraneous cognitive load, it is related to user evaluation. Improvement strategies are proposed for three cognitive behaviors combined with the cognitive load effects: classification, comparison and quantification.

Strategy 4: For the classification process. Since the individual presentation is disordered in the TIED, the actual presentation of individuals with high cognitive similarity is random to the user in the system. Users spontaneously integrate and process the locations of similar individuals in working memory, which is similar to the processing of information scattered in the spatial or temporal dimension described by the split-attention effect. The classification in the user evaluation is caused by the scattered layout of similar information. Therefore, according to the user cognitive similarity, the individuals should be presented in order.

Strategy 5: For the comparison process. Since the population size is usually 6–12 in the TIED, the comparison between individuals requires users to process multiple information simultaneously in working memory, which consumes many cognitive resources. This is similar to the problem targeted by the isolated interacting elements effect. The cognitive load caused by parallel processing can be reduced through the controlled presentation of information. Accordingly, the evaluation process should be improved to reduce the number of users processing information simultaneously.

Strategy 6: For the quantification process. This process requires users to express their individual preference with an accurate number. For experienced experts, when dealing with problems closely related to rational decision-making, the assignment of a specific value helps computers obtain their precise preferences and judgments. The evolutionary efficiency is improved and the quality of the output schemes is ensured. However, the design activity itself is accompanied by emotional decision-making; the participation of human intuition and feeling is unavoidable. It is difficult to quantify them. In addition, from the perspective of the IGA, the accurate fitness value is not necessary for evolution. What is required for the algorithm evolution is the user's preference related to the individuals. The assignment of specific values is only a representation method of the preference relationship. Therefore, from the perspective of user cognition and algorithm, the assignment operation is redundant to the user evaluation process itself. Accordingly, appropriate mechanisms should be adopted to improve the individual evaluation process, such as the methods mentioned in Sect. 2.1.

The intrinsic cognitive load is related to chromosome encoding rules, crossover rate, and mutation rate settings. As mentioned in Sect. 3.2, the smaller the number of chromosomes, the smaller the search range of the solutions, which leads to a mismatch between the final output schemes and the design objectives. However, from the perspective of user cognition, the fewer the number of chromosomes, the easier the user's tasks. Therefore, the strategy 7 is proposed:

Strategy 7: The chromosome encoding rules should be formulated combined with the cognitive ability of the user group and the characteristics of the actual design problem; The crossover rate and mutation should be determined based on the comprehensive consideration of the algorithm convergence speed and searchability for the unknown domain.

4 Experiments and Discussions

4.1 Algorithm Selection

To verify the proposed strategies above, two improved IGA algorithms were chosen. These two algorithms are respectively aimed at improving the cognitive process in the early stage of evolution and the process of user evaluation.

CA-IGA. The CA-IGA builds on our previously proposed method [31], retaining its improved parts in the construction of association cognition. And a novel idea is added based on the proposed strategies. The algorithm flow is shown in Fig. 7, which includes three improved parts: the associative construction of "design objective-reference case", the associative construction of "reference case-individual characteristic", and the adaptive presentation of reference information.

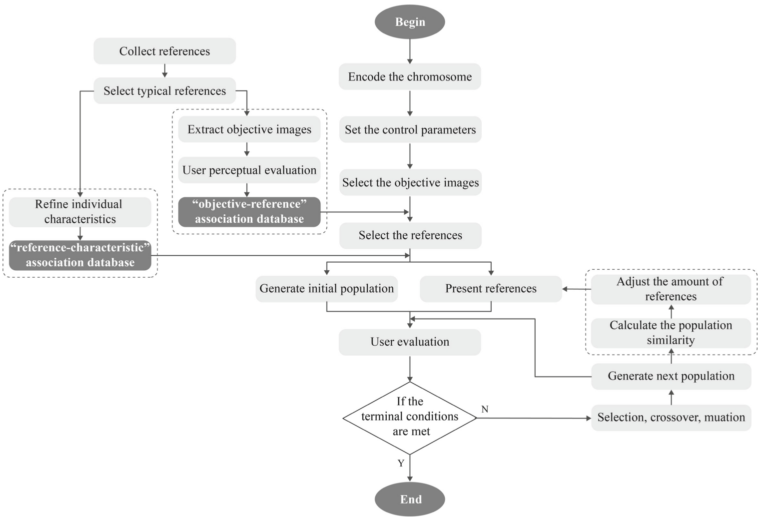

Fig. 7. Flow chart of CA-IGA

In the algorithm design of the CA-IGA, the associative construction of "design objective-reference case" reflects the idea of Strategy 1; the association construction of "reference case-individual characteristics" reflects the idea of Strategy 2; the adaptive number of references is presented, which embodies the idea of Strategy 3. Therefore, the CA-IGA can be used to validate the improvement strategies for the germane cognitive load in Sect. 3.3.

AR-IGA. The AR-IGA was the method we proposed, and its specific algorithm design is in the literature [32]. Its algorithm flow is shown in Fig. 8, including three improvements: the evaluation based on the alternation ranking method, the calculation of individual fuzzy fitness, and the comparison based on fuzzy fitness.

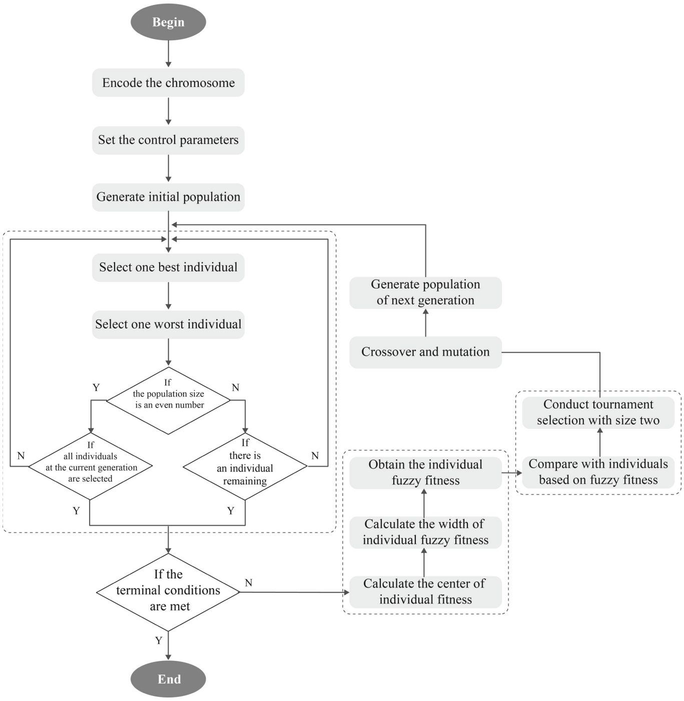

Fig. 8. Flow chart of AR-IGA

The algorithm design of the AR-IGA embodies the idea of strategies 5 and 6. By improving the evaluation mechanism and procedure, the AR-IGA reduces the amount of information that users need to process simultaneously and avoids the assignment and scoring operation. Thus, the AR-IGA can be used to validate the part of the improvement strategies for the extraneous cognitive load in Sect. 3.3.

4.2 Chromosome Encoding

The road roller painting was selected as a case study. Based on product research, the functional parts and painting area were determined. Then, the style of each painting area was summarized, and the value range of the dominant and auxiliary colors was defined. Finally, based on the proportion of phenotypes, the styles of each painting area, the values of the dominant and auxiliary colors, and the specific positions of the logo and product model were encoded, as shown in Fig. 9.

Based on the coding rules of each part, the chromosome encoding was formulated, as shown in Fig. 10. The genotype of an evolutionary individual is a binary string of 27 bits, where the first 4 bits express the dominant color, the 5th and 6th bits express the auxiliary color, the 7th, 8th, 9th, and 10th respectively express the color of the vibrating drum, the rear frame, the bumper, and the hub, the 11th to 14th bits express the painting style of the cab, the 15th to 18th bits express the painting style of the front frame, the

19th to 22nd bits express the painting style of the hood, the 23rd to 25th bits express the location of the logo, and the 26th and 27th bits express the location of the product model identification.

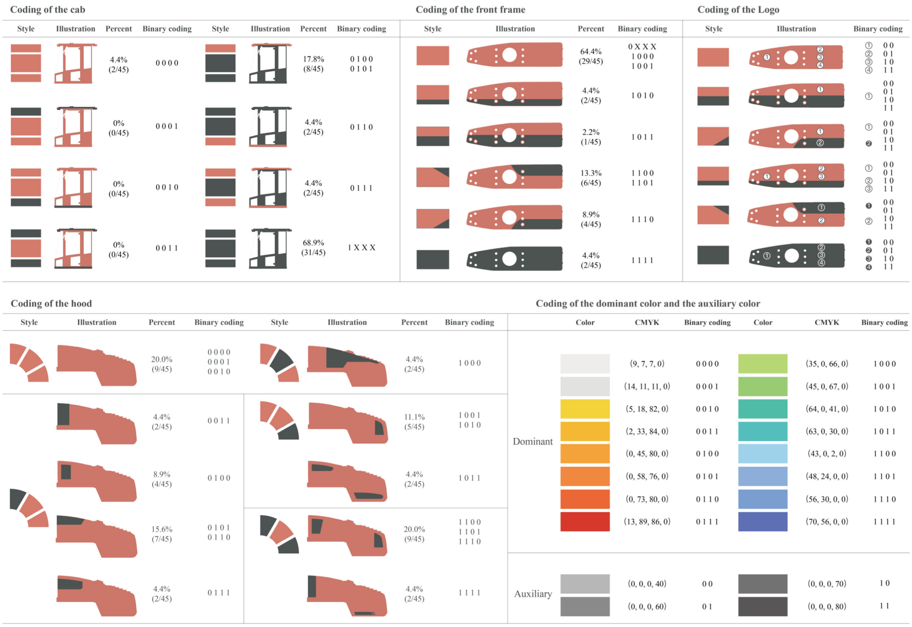

Fig. 9. Chromosome encoding of each part

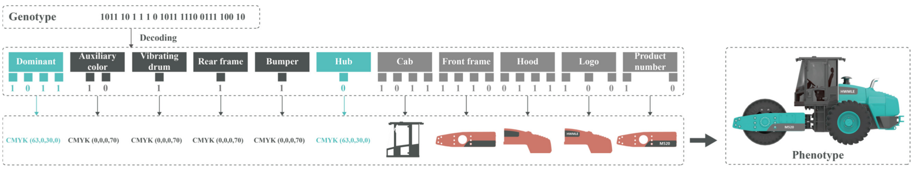

Fig. 10. Relationship between the genotype and phenotype of an individual

4.3 Parameter Setting and Terminal Condition

The population size N is set to 6. The maximum number of generation T is set to 16. One-point crossover and one-point mutation mechanisms are adopted, and their rates are 0.6 and 0.03. The maximum fitness f_{max} is 9, and the minimum fitness f_{min} is 0. In the CA-IGA, the mid-evolution threshold o_1 and late-evolution threshold o_2 are set to 1/3 and 2/3. In the AR-IGA, w_{max} is set to 0.288, and α_{min} is set to 0.5.

The terminal conditions are as follows: (1) users find four satisfactory schemes, and (2) the number of generations reaches 16. Once one of the two is met, the evolutionary process ends. If users do not find four satisfactory schemes until the generation is 16, it is believed that the algorithm cannot achieve convergence in this evolutionary iteration.

4.4 System Interface

Three IED systems were developed based on the TIGA, the CA-IGA, and the AR-IGA. The interfaces are shown in Fig. 11.

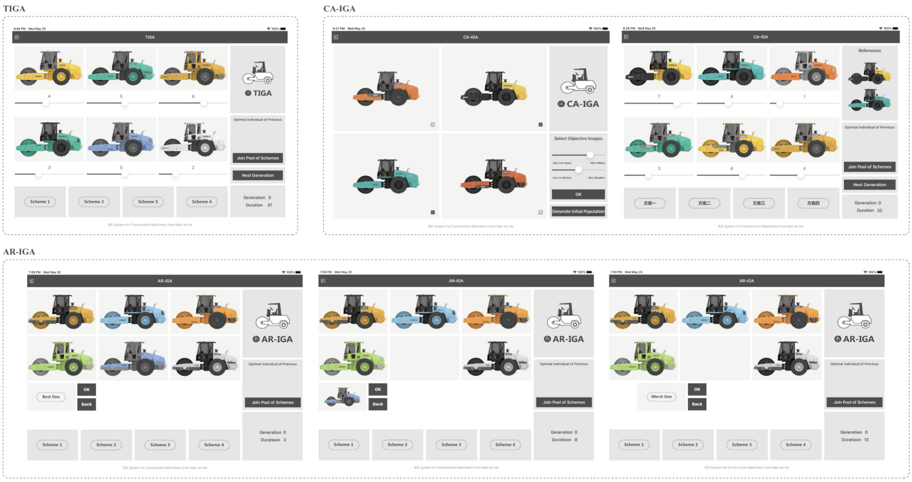

Fig. 11. System interfaces based on three algorithms

4.5 Experimental Design

Ten graduate students (six males, four females, average age 24.3, standard age difference of 1.3) majoring in industrial were invited as the subjects. A color blindness test was performed to understand the color discrimination ability of the subjects. The subjects operated the IED systems for the road roller painting based on three methods (TIGA, CA-IGA, and AR-IGA). None of the subjects had engaged in work or research related to the painting design. Only one method is tested at a time. The experiments were approved by the University Ethics Committee, and all subjects received written consent before participating in the study. The two experiments are spaced three days apart to avoid the influence of the previous experiment. Before each experiment, the subjects need to learn the system operation to ensure that the subjects can operate the system proficiently.

4.6 Evaluation Indicator

Integrating the evaluation indicators of the IED and the cognitive load measurement, this paper proposed an evaluation method that comprehensively considers the algorithm convergence and the cognitive load measurement. The evaluation indicators are shown in Fig. 12.

In the related studies, the algorithm convergence is usually reflected in the number of generations. The smaller the number of generations when other parameters are fixed, the smaller the number of algorithm iterations, and the faster the convergence. However, too rapid convergence can make the evolution premature.

The measurement of cognitive load in the IED is a combination of the subjective and objective assessment. For the subjective evaluation of the cognitive load, Leppink *et al.* [33] pointed out that the National Aeronautics and Space Administration Task Load Index (NASA-TLX) has better applicability for cognitive load measurement in a variety of scenarios. Furthermore, the NASA-TLX scale is one of the most widely used subjective psychological stress assessment tools [34], with high user acceptance and low participant variation [35]. Therefore, the NASA-TLX was adopted to evaluate the total cognitive load level.

For the objective evaluation of cognitive load, the time for evaluating first-generation is used to reflect the germane cognitive load level, the average time for evaluating an individual is used to reflect the extraneous cognitive load level, and the total time and the number of individuals evaluated are used to reflect the total cognitive load level.

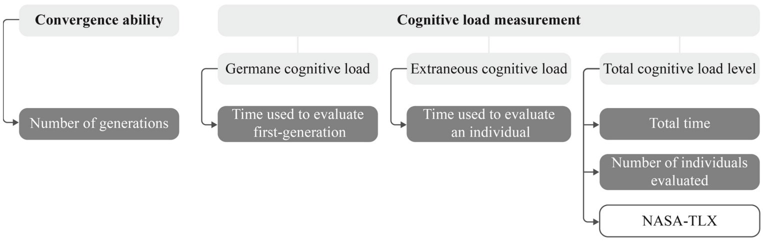

Fig. 12. Evaluation indices for IED combined with cognitive load measurement

4.7 Analysis and Discussion

The data mentioned in Sect. 4.6 were recorded. The number of generations and the number of individuals evaluated is listed in Table 1. The time used for the first generation and the total time are listed in Table 2. A paired-sample T test is suitable for studying the differences in results of the same subject under different treatments. Thus, this method is adopted to compare the effects of three different methods on the subjects' task completion.

In IBM SPSS Statistics 26, the number of generations and the number of individuals evaluated of three methods were compared by using a paired-sample T test. The results are shown in Table 3. For the number of generations, the difference between the TIGA and the CA-IGA in t is 3.50, and $P = 0.007 < 0.05$. It can be seen that the CA-IGA has a significant effect on the number of generations compared to the TIGA, and the average is reduced by 1.10. In the same way, AR-IGA has a significant impact on the number of generations compared to the TIGA and the CA-IGA, with 2.70 and 1.60 less. For the number of individuals evaluated, the difference between the TIGA and the CA-IGA in t is 3.19, and $P = 0.011 < 0.05$. It can be seen that the CA-IGA has a significant effect on the number of generations compared to the TIGA, and the average is reduced by 6.70. In the same way, AR-IGA has a significant impact on the number of individuals evaluated compared to the TIGA and the CA-IGA, with 13.70 and 7.00 less.

The time used for the first generation and the total time of the three methods were compared. The results are shown in Table 4. For the time used for the first generation, the difference between the TIGA and the CA-IGA in t is 7.31, and $P = 0.000 < 0.05$. It can be seen that the CA-IGA has a significant effect on the number of generations compared to the TIGA, and the average is reduced by 11.60 s. In the same way, AR-IGA has a significant impact on the number of generations compared to the TIGA with 8.80 s shorter. And the CA-IGA is 2.80 s less than the AR-IGA. For the total time, the CA-IGA is 53.60 s less than the TIGA. The AR-IGA is 133.30 s less than the TIGA and 79.70 s less than the CA-IGA.

Based on the number of individuals evaluated and the total time in Table 1 and Table 2, the average time used to evaluate an individual is calculated in Table 5. The average time of the three methods was compared, and the results are shown in Table 6. The CA-IGA is 0.41 s less than the TIGA. The AR-IGA is 1.42 s and 1.01 s less than the TIGA and the CA-IGA, respectively.

The results of the NASA-TLX scale evaluated by the subjects were averaged to reflect the total cognitive load level, as shown in Table 7. The total cognitive load level of the three methods was compared, and the results are shown in Table 8. Compared with the TIGA, CA-IGA decreases by 2.84. Similarly, the AR-IGA is 12.08 and 9.24 fewer than the TIGA and the CA-IGA.

The above results were discussed. From algorithm convergence, the CA-IGA is less than the TIGA in the number of generations. It indicates that the associative construction strategy helps users clarify the objective image, and their individual evaluation results are more consistent with the design objectives. Compared with the TIGA and the CA-IGA, the number of generations of AR-IGA decreases. It demonstrates that the alternation ranking method helps users clarify the pros and cons between individuals, which prevents deviations in the evolutionary direction.

For the germane cognitive load at the early evolution, the CA-IGA takes less time to evaluate the first generation than the TIGA and the AR-IGA. It shows that associative construction helps users build the mapping relationship between design objectives and individual characteristics, thereby alleviating the cognitive fatigue of initial evaluation. On the other hand, the references selected by users directly influence population initialization, which improves the consistency of the initial population and design objectives.

Table 1. Number of generations and number of individuals evaluated in the three methods

Subject	Number of generations			Number of individuals evaluated		
	TIGA	CA-IGA	AR-IGA	TIGA	CA-IGA	AR-IGA
1	10	9	9	57	53	54
2	9	9	8	53	54	48
3	11	10	6	66	60	36
4	9	9	7	51	51	42
5	9	8	7	51	48	42
6	11	9	6	66	53	36
7	11	9	6	63	48	36
8	12	9	8	63	46	48
9	8	8	7	47	47	42
10	12	11	11	70	60	66

Table 2. Time used for first generation and total time by the three methods

Subject	Time used for first generation			Total time		
	TIGA	CA-IGA	AR-IGA	TIGA	CA-IGA	AR-IGA
1	36	32	38	320	271	203
2	47	27	32	316	244	208
3	43	30	34	329	316	160
4	41	28	31	302	279	194
5	45	35	37	308	240	168
6	41	37	35	336	246	131
7	35	25	27	310	224	101
8	30	17	22	277	205	150
9	39	22	23	241	227	175
10	30	18	20	274	225	190

Table 3. Paired-sample T test of number of generations and number of individuals evaluated with the three methods

	Difference	Mean	t	Sig. (2-Tailed)
Number of generations	TIGA vs. CA-IGA	1.10	3.50	0.007
	CA-IGA vs. AR-IGA	1.60	3.75	0.005
	TIGA vs. AR-IGA	2.70	4.67	0.001
Number of individuals evaluated	TIGA vs. CA-IGA	6.70	3.19	0.011
	CA-IGA vs. AR-IGA	7.00	2.45	0.037
	TIGA vs. AR-IGA	13.70	3.89	0.004

Table 4. Paired-sample T test of time used for first generation and total time with the three methods

	Difference	Mean	t	Sig. (2-Tailed)
Time used for first generation	TIGA vs. CA-IGA	11.60	7.31	0.000
	CA-IGA vs. AR-IGA	−2.80	−3.77	0.004
	TIGA vs. AR-IGA	8.80	5.63	0.000
Total time	TIGA vs. CA-IGA	53.60	5.89	0.000
	CA-IGA vs. AR-IGA	79.70	6.29	0.000
	TIGA vs. AR-IGA	133.30	8.78	0.000

Table 5. Average time taken to evaluate an individual by the three methods

Subject	TIGA	CA-IGA	AR-IGA
1	5.6	5.1	3.8
2	6.0	4.5	4.3
3	5.0	5.3	4.4
4	5.9	5.5	4.6
5	6.0	5.0	4.0
6	5.1	4.6	3.6
7	4.9	4.7	2.8
8	4.4	4.5	3.1
9	5.1	4.8	4.2
10	3.9	3.8	2.9

Table 6. Paired-sample T test of the average time taken to evaluate an individual with the three methods

	Difference	Mean	t	Sig. (2-Tailed)
Average time taken to evaluate an individual	TIGA vs. CA-IGA	0.41	2.48	0.035
	CA-IGA vs. AR-IGA	1.01	6.97	0.000
	TIGA vs. AR-IGA	1.42	9.13	0.000

Table 7. Total cognitive load level of the three methods

Subject	TIGA	CA-IGA	AR-IGA
1	42.5	37.5	26.7
2	40.8	40.0	31.7
3	39.2	37.5	33.3
4	41.7	39.2	28.3
5	45.0	42.5	31.7
6	42.5	40.8	31.7
7	39.2	36.7	30.8
8	40.0	38.3	29.2
9	45.0	40.8	29.2
10	43.3	37.5	25.8

Table 8. Paired-sample T test of the total cognitive load level with the three methods

	Difference	Mean	t	Sig. (2-Tailed)
Total cognitive load level	TIGA vs. CA-IGA	2.84	5.54	0.000
	CA-IGA vs. AR-IGA	9.24	11.64	0.000
	TIGA vs. AR-IGA	12.08	10.28	0.000

For the extraneous cognitive load at the evaluation stage, the AR-IGA takes significantly less time to evaluate an individual than the TIGA and the CA-IGA. It shows that the alternation ranking method simplifies the user evaluation operation, thereby reducing the cognitive load of the evaluation process.

For the total cognitive load level, the number of individuals evaluated for the AR-IGA is significantly reduced compared with the TIGA and the CA-IGA. The total time of the AR-IGA is also reduced compared with the TIGA and the CA-IGA. This is also consistent with the results of the NASA-TLX scale.

Therefore, from the perspective of algorithm convergence and cognitive load, the AR-IGA has advantages in algorithm convergence, reducing the extraneous cognitive load and the total cognitive load level; the CA-IGA has advantages in improving the efficiency of associative cognition in the early-evolutionary period. These can prove the effectiveness of the proposed strategies to a certain extent.

5 Conclusions

This paper systematically analyzed the user cognitive process in the IED, and proposed the corresponding improvement strategies based on cognitive load effects. The effectiveness of the strategies was verified by system development and user experiments. However, the study in this paper has the following limitations: First, the study of cognitive processes is mainly based on theoretical research, and the physiological and psychological data related to the user cognitive activities in the IED are not studied. And the follow-up should be combined with eye movements, EEG measurements and other methods to conduct a comprehensive analysis of the user cognitive process in the IED. In addition, two algorithms were selected in this paper to verify certain proposed strategies, but not all are verified. And the actual improved algorithm research is not carried out based on the strategies in this paper. The next step should be to design the corresponding improvement algorithm to verify and correct the proposed strategies.

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