preference to certain gene units of evolutionary individuals.

3 System Design

The flowchart of system design is shown in Fig. 2. It can be seen that various design model are stored in specific elements database. At first, the system selects the models of every part and combines the models to some individual designs. The population evolutionary individual is displayed in users' interface in the graphic form, and their fitness is given by the users. And then in view of the fitness of every evolutionary individual, their population are duplicated, mutually crossed, mutated and generated the next generation by the system; the results are still displayed in users' interface in the graphic form. At the same time, artificial neural network continues to learn the users' knowledge till the learning precision meets the requirement, and then it replaces the users to evaluate evolutionary individual and generate the next generation by crossover and mutation. The above process iterates to generate the population with much higher fitness. Nevertheless, once the populations are evolved to certain stage, the difference in the individuals' fitness will be less and less, and it will be not effective to search at this stage. Then, the populations are evolved into local search stage. The users appoint the searching area, and the evolutionary individual will be generated the next generation by crossover and mutation. In the meanwhile, according to local search area selected by users, the system searches for the most optical individual of users' similar preference. The two types of individuals are both displayed in users' interface in the graphic form to generate population with higher fitness and better design.

3.1 Interacting with Users by GUI

Users could achieve man-machine interaction by graphical interfaces. Before man-machine interaction, the individual (console) has been separated into several modules (every module stands for a gene unit) and encoded. Before evaluating, users can weight each gene unit, in other words, users attach different importance to different gene units. Just like the case in the paper, users might regard steering wheel and instrument panel more important, so their weights are defined as 0.2, and the rest are 0.15. For the sake of easy computation, mean weights are set up in the paper with no influence on the system efficiency. After decoded, the individuals are showed by graphical interface in 2D form; additionally, the 3D pictorial button is also equipped for users. If the users are interested in some individual, they could have 3D picture by pressing the 3D button. Users need to evaluate every picture before artificial neural network finishes learning about the users' demands; once it has grasped the user' demands, they could choose artificial neural network to facilitate assess. After users' evaluation or neural network's evaluation, new pictures of a new generation will be displayed in the graphic interface. And once the users have evaluated these pictures, the neural network will automatically learn how to modify the forecast of the system with its new evaluation, further it will improve assessed value, speed up convergence and provide data for system to learn. In each step, the graphical interface is applied by the system to evolve individuals. By iterating the above process, the evolutionary individual with higher fitness could be generated, i.e. better design is realized; users' satisfactory picture will be obtained by repeating the process.

3.2 Flow and Steps of the Algorithm

According to the designed system structure, the author devises the following algorithm flow and step in Fig. 3.

Arithmetic steps:

Step 1: to set arithmetic controls parameter;

Step 2: to generate initialized population;

Step 3: to decode and show to users in graphic form; user evaluates evolutionary population;

Step 4: whether the users are satisfied or not, if they are, to output the optimal solution, and the algorithm ends; if not, turn to step 5;

Step 5: the system inquires the users whether they continue to evaluate individuals; if they are, turn to step 6, and if not turn to step 7;

Step 6: to carry out genetic manipulation, generate a new generation population, turn to step 3;

Step 7: the system uses artificial neural network to evaluate evolutionary individual in stages, and uses hierarchical IGA to search locally; genetic manipulation is carried out in inner system to generate a new generation population; the system defines the individuals' fitness;

Step 8: to submit the optimal individual of the evolutionary population;

Step 9: whether the users need co-evolution or not? If they do, according to the above (2), choose out users with the similar preference, and turn to step 10; if not, turn to step 11;

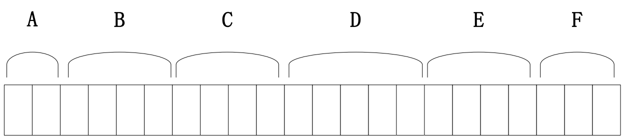
Step 10: to visit the optimal individuals of evolutionary population where the users with the similar preference are.

Step 11: whether the current users are satisfied with the individual or not; if they are, the algorithm ends, and if not, users evaluate the individual, and turn to step 6.

4 System Application

4.1 System Application

On the basis of the above description about the system, it is necessary to clearly understand every element of the evolutionary individuals. Therefore, the paper introduces gene unit and allele unit, and encodes detail model. At first, the common detail factors in Fig. 1 are re-divided into five sections shown in Fig. 4, and they are the whole composition of console, steering wheel, instrument panel, SZM and gear shift lever. And then, the five parts are encoded, in which three bits are added for whole color style to choose. Every part and the color style consist of a design. The users' favorite design combination could be figured out by using IGA, and more rational design will be generated. The details of encoding will be illustrated as follows. Given the limited space, only steeling wheel and SZM taking for instance in the paper.



A: Console Whole Composition Section
B: Steering Wheel Section
C: Instrument Panel Section
D: SZM Section
E: Gear Shift Lever Section
F: Color Style Section

Fig. 4. Encoding Module

- Console whole composition section: including the framework design of console and air outlet; totally four models; encoded by 2 bits.
- Steering wheel section: as shown in 4-3, including steering wheel, horn button, steering lamp, headlight button, as well as the trigger buttons of headlight, wiper and other function keys button; totally four models; encoded by 4 bits.
- Instrumental panel section: including tachometer, speedometer, and some display screens of the other status of cars; totally sixteen models; encoded by 4 bits.
- SZM section: as shown in 4-4 covering navigator, music player, the adjust button of air-condition, car telephone, the button of caution light for danger and other function keys; totally twenty-six models besides wireless navigator and car telephone; encoded by 5 bits.
- Gear shift lever section: including shift level of transmission, parking brake, ashtray, cigarette lighter and other function keys; totally nine models; encoded by 4 bits.

Thereby, it is necessary to add three bits to complete chromosome coding so that the users could choose their favorite color in the 8 selective color styles. A wholly encoding chromosome is shown in figure in 4-6. By computing all the combinations of the designs and its corresponding color, the size of search room is worked out as 1,437,696 ($4\times12\times16\times26\times9\times8=1,437,696$), from which the optimal design will be searched out according to the users' preference and mood feedback.

4.2 Users' Interface

In order to ease the interaction between the users and the system, it is essential for the system to display 3D graphics for users. At first, a 3D model for each component element of the design should be established, and Fig. 5 has shown an example of 3D model for steering wheel to reveal the 3D model; then the combined 3D model will consequently be shown by the system on the basis of decoding of individual gene type. The current evolutionary individual is displayed in the screen by the system, just like what are demonstrated in Fig. 6. Below the design of every evolutionary individual, a slider is used to achieve users' feedback or preference. Besides, the current evolutionary individuals' status is revealed in the users' interface: the optional individual in the last generation and the current optional individual, so are the control buttons of "into next generation" and "use ANN to evaluate", as well as other information for users to operate in the interface. Hence, by interacting with the system, the users could find out their favorite design in the larger searching room.

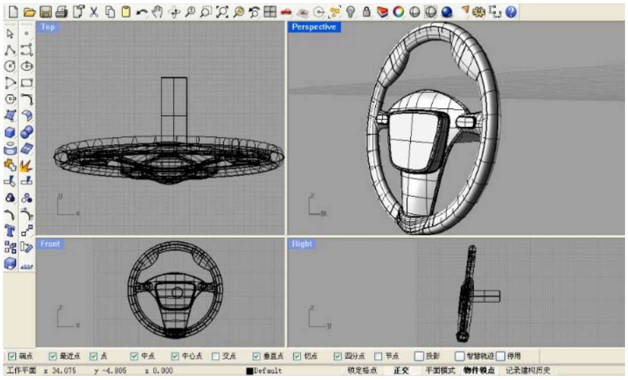


Fig. 5. Constructive Process of 3D Model of Steeling Whale

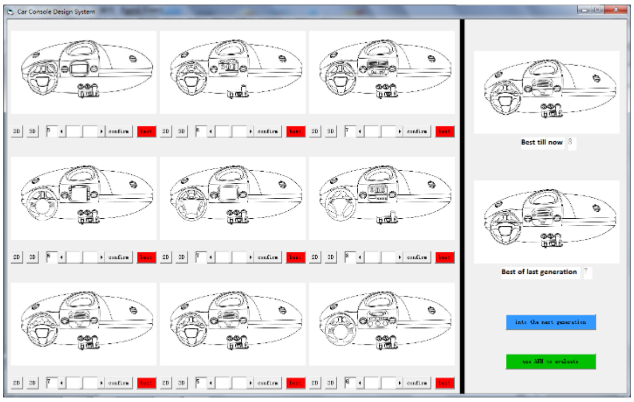


Fig. 6. Main Interface of Interaction

4.3 Performance Analysis

As IGA design system is used to reduce the frequency for human to evaluate the evolutionary individual, so as to lighten their fatigue, and its usage to lower users' fatigue is analyzed here to testify its effect.

In the paper, N is deemed as the range of evolutionary population; T as the number of ending evolutionary generation, T_1 as the number of evolutionary generation before the environment is stable, T – T_1 as the number of evolutionary generation after the environment is stable. In the traditional IGA, NT is set as the number of evolutionary individuals evaluated by users before their evolution ends.

At first, IGA based on artificial neural network is discussed. In the two stages the number of sample needing learning is set as $2N_1$; the number of sample needing testing the learning effect of neural network as 2Nt; both of which could be obtained by the users evaluating evolutionary individuals, in other words, the number of evolutionary individuals evaluated by users is deemed as $2(N_1+N_t)$. In the evolutionary process, the total amount of evolutionary individuals evaluated by users is $NT_1+ 2(N_1+N_t)$, thereby, the fact that some evolutionary individuals are evaluated by neural network makes the number of evolutionary individuals not evaluated by human as NT - $(NT_1 + 2(N_1 + N_t))$, i.e. N $(T - T_1) – 2(N_1 + N_t)$. It is observed that regarding IGA based on artificial neural network, the key effect of artificial learning is to lower users' fatigue. In the next part, the degree for hierarchical IGA to ease users' fatigue is analyzed. As IGA in the whole searching stage has the same efficiency when directly used, only its efficiency in local searching stage is specialized on in the paper.

In local searching area, the maximum of individual with allele unit is K_{lj}. Actually, the optimal individual is reserved, and the worst individual is replaced in the evolutionary process. As hierarchical IGA is a kind of search based on population, it surely could seek out the optimal solution after K_{lj} –(N – 1) iteration at most; While by using IGA directly, it usually needs K_{lj} iteration to certainly work out the optimal solution in local searching area with K_{lj} allele unit.

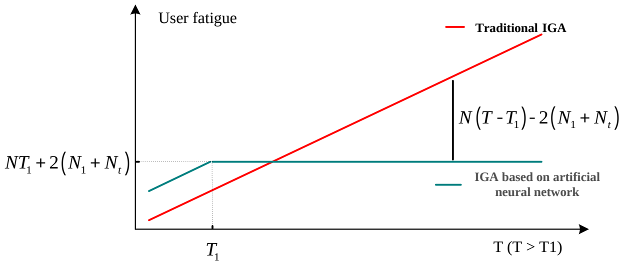


Fig. 7. Users' Fatigue Analysis

It can be easily seen from Fig. 7 that when the evolutionary generation number T increases, the evolutionary generation number evaluated by humanNT_1 + $2(N_1+N_t)$ still remains the same; therefore, the users' fatigue doesn't increase. It usually goes N > 1, so K_{lj} - (N – 1) < K_{lj} could be speculated, which means the arithmetic could increase the evolutionary generation number without increase users' fatigue. Once combined with hierarchical IGA, IGA based on artificial neural network could greatly enhance the number of evolutionary generation to offer the better evolutionary individual in wholly searching stage; in the local searching stage, as it is easy to discriminate the difference in the individual, it could provide more accurate fitness to improve its precision. As a result, to integrate two kinds of arithmetic could not only guarantee the enough evolution generation but also make the users gain their satisfactory product design in the possibly short time. In addition, nowadays the internet technology develops at high speed; if collaborative IGA is used to search the users with similar preference to provide product reference, the convergence of population will be further speeded up, and the diversity of product will be enriched.

5 Conclusion

In order to lighten the users fatigue in IGA, the method of evaluating individual fitness based on artificial neural network, as well as the method of combination of hierarchical IGA orientating population evolution and collaborative IGA based on user preference, is brought forward in the paper to realize the users' design system of car console. All based on the disintegration of the evolutionary individual gene unit of sense, the above methods use individual information to evaluate the allele unit of sense fitness of every gene unit of sense, further the allele unit of sense fitness to evaluate individual fitness, and then the gene unit of sense to spread the whole individuals' fitness for users to evaluate. In this way, they could better orientate population evolution to reduce evolution generation number and save the system's resources; as a matter of fact, the essence of the methods is to extract and apply the knowledge in the evolutionary process. The arithmetic works on the premise that the individual gene type is disintegrated into gene units of sense, so their usage is confined; however, in most situation, there is no adversary influence on their use just like the design of car console in the paper; the individual gene type could be divided to 5 gene units of sense: console whole composition, steering wheel instrument panel, SZM, gear shift lever and color style. Additionally, the users could weight every gene units of sense consisting of individual, which makes the evolutionary individual better to satisfy the users' preference. In consequence, much more satisfactory products are designed for users. To sum up, this method relieves users' fatigue, and it is more appropriate to satisfy the users' demand by interacting with them and can be researched further widely.

Meanwhile, the design system with users' participation put forward in the paper meets their individualized demand. It integrates customers' affection into the operation process of car console layout design so that their really satisfactory product is customized, and it provides a new method for many manufacturers to quickly and accurately gain customers' preference and requirement which makes them more competitive in the market. The design system efficiently breaks the ice that it is hard to surmise customers' preference and the product is too monotonous in car industry. Further, it opens up new direction for future development in car industry. With wide application prospect, the method is also suitable to other manufacturing industries, such as clothes, furniture and etc. In near future, it is believed that the customers could customize their favorite product design for food, clothing, shelter and transportation from product design manufacturing enterprises which manufacture their product according to their customized product design.

Acknowledgment

This work was part of the Program on Natural Science Fund of China, Interactive Collaborative Optimization of Complex Products Configuration Design for Mass Customization, funded under the National Natural Science Foundation of China, grant number 71201115.

References:

[1] J. Jiao, Y. Zhang, and M. Helander, A Kansei Mining System for Affective Design, *Expert Systems with Application*, Vol. 30, No. 4, 2006, pp. 658–673.

[2] J. R. Chou, Applying a Creativity-Based Design Process to New Product Development, PhD Dissertation, National Cheng Kung University, 2004, Taiwan.

[3] S. Staines A., Neri F. (2014). "A Matrix Transition Oriented Net for Modeling Distributed Complex Computer and Communication Systems". WSEAS Transactions on Systems, 13, WSEAS Press (Athens, Greece), 12-22.

[4] Seongah Chin, and Kyoung-Yun Kim, Facial Configuration and BMI Based Personalized Face and Upper Body Modeling for Customer-Oriented Wearable Product Design, *Computers in Industry*, Vol. 61, No. 6, Aug. 2010, pp. 559-575.

[5] RajiSrinivasan, Gary L. Lilien et al. The Total Product Design Concept and an Application to the Auto Market, *Journal of Product Innovation Management*, Vol. 29, No. S1, Dec. 2012, pp. 3-20.

[6] H. M. Khalid, and M. G. Hollander, A Framework for affective Customer Needs in Product Design, *Theoretical Issues in Ergonomics Science*, Vol. 5, No. 1, 2004, pp. 27–42.

[7] M. L. Chang, and J. H. Lee, Symbiosis: Creativity with Affection, *Lecture Notes in*

Artificial Intelligence, Vol. 4562, 2007a, pp. 32–41.

[8] Michael G. Luchs, Jacob Brower, and Ravindra Chitturi. Product Choice and the Importance of Aesthetic Design Given the Emotion-Laden Trade-Off between Sustainability and Functional Performance, *Journal of Product Innovation Management*, Vol. 29, No. 6, Dec. 2012, pp. 903-916.

[9] Dou Runliang, Zong Chao. Application of Interactive Genetic Algorithm based on hesitancy degree in product configuration for customer requirement. International Journal of Computational Intelligence Systems. 2014, Vol. 7. pp. 74-84, p.11

[10] Camilleri M., Neri F., Papoutsidakis M. (2014). "An Algorithmic Approach to Parameter Selection in Machine Learning using Meta-Optimization Techniques". WSEAS Transactions on Systems, 13, WSEAS Press (Athens, Greece), 202-213.

[11] K. A. Hsiao, and L. L. Chen, Fundamental Dimensions of Affective Responses to Product Shapes, *International Journal of Industrial Ergonomics*, Vol. 36, No. 6, 2006, pp. 553–564..

[12] G. Pahl, and W. Beitz, Engineering Design-A Systematic Approach, Springer, 1996.

[13] X. Y. Liu, W. P. Wang, H. Liu, et al, Particle Swarm Optimization Based on Dynamic Niche Technology with Applications to Conceptual Design, *Computer Science*, Vol. 33, No. 10, 2006, pp. 163-168 and p. 209.

[14] A. M. Brintrup, J. Ramsden, H. Takagi, et al. Ergonomic chair design by fusing qualitative and quantitative criteria using interactive genetic algorithms, *IEEE Trans on Evolutionary Computation*, Vol. 12, No. 3, 2008, pp. 343-354.

[15] Dan Nathan-Roberts, and Yili Liu, Investigation of Relative Mobile Phone Size Preference Using Interactive Genetic Algorithms, in *Proceedings of Human Factors and Ergonomics Society Annual Meeting*, 2010, pp. 1807-1811.

[16] Bandte Oliver, A Broad and Narrow Approach to Interactive Evolutionary Design—an Aircraft Design Example, *Applied Soft Computing*, Vol. 9, No. 1, 2009, pp. 448-455.

[17] M Papoutsidakis, D Piromalis, F Neri, M Camilleri (2014). "Intelligent Algorithms Based on Data Processing for Modular Robotic Vehicles Control". WSEAS Transactions on Systems, 13, WSEAS Press (Athens, Greece), 242-251.

[18] H. Zhu, S. F. Wang, and Z. Wang, Emotional Music Generation Using Interactive Genetic Algorithm, in *International Conference on Computer Science and Software Engineering*, Wuhan, 2008, pp. 345-348.

[19] M. Q. Li, B. Y. Xu, and J. S. Kou, The Combination of Genetic Algorithm and Neural Network, *Theory and practice of systems engineering*, Vol. 19, No. 2, Feb. 1999, pp. 66-70 and p. 113.

[20] G. W. Gong, G. S. Hao, Y. Zhou, and Y. N. Guo, *The Principle and Its Application of Interactive Genetic Algorithm*, National Defence Industry Press, Beijing, Jan. 2007.

[21] X. Y. Sun, J. Ren, D. W. Gong, Interval-Fitness Interactive Genetic Algorithms with Varying Population Size Based on Semi-Supervised Learning, *Control Theory & Applications*, Vol. 28, No. 5, May. 2011, pp. 610-618.

[22] D. W. Gong, and J. Yuan. Large Population Size Iga with Individuals' Fitness not Assigned by User, *Applied Soft Computing*, Vol. 11, 2011, pp. 936-945.

[23] Y. Zhou, D. W. Gong, G. S. Hao, et al, Neural Network Based Phase Estimation of Individual Fitnessin (Interactive) Genetic Algorithm, *Control and Decision*, Vol. 20, No. 2, 2005, 234-236.

[24] M. Q. Li, and J. S. Kou, Coordinate Multi-Population Genetic Algorithms for Multi - Model Function Optimization, *Acta Automatica Sinica*, Vol. 28, No. 4, 2002, pp. 497-504.

[25] H. Takagi, Active user intervention in an EC search, in *Proceedings of the 5th Joint Conference on Information Sciences*, 2000, pp. 995-998.

Appendixes

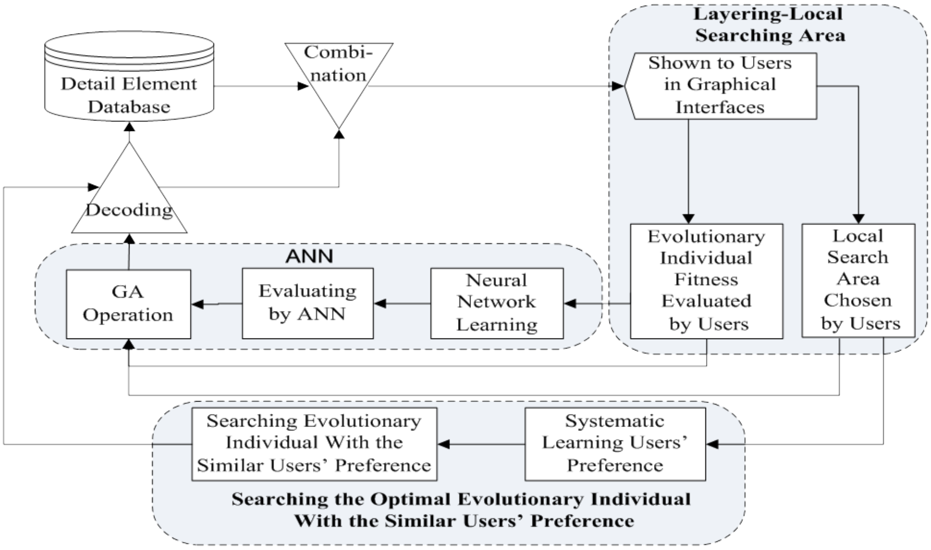


Fig. 2. System Flowchart

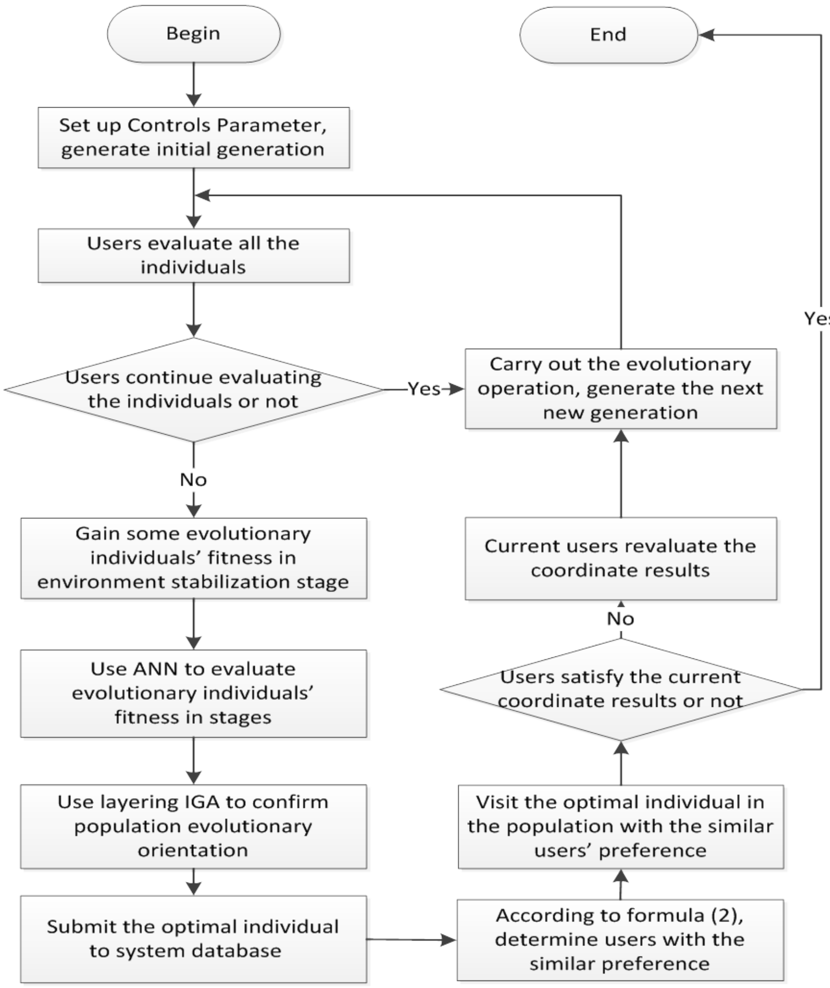


Fig. 3. Algorithm Flow