A New Aesthetic Evolutionary Approach for Jewelry Design

Somlak Wannarumon[1, 2] and Erik L. J. Bohez[2]

[1]Naresuan University, Thailand, somlakw@nu.ac.th
[2]Asian Institute of Technology, Thailand, bohez@ait.ac.th

ABSTRACT

This paper presents a new evolutionary approach to create non-functional art forms for jewelry design. The proposed EA is hybrid between EP, ES, GA and GP. Art forms are represented by using Iterated Function Systems (IFS) fractal for jewelry ring's ornaments. IFS are encoded in form of chromosomes. Mutation and crossover operators are developed to increase variations of art forms. Two-step fitness function is developed. The first step is morphological fitness function to evaluate compactness and connectivity of art forms. This fitness function screens the incompact and disconnected art forms out of the evolutionary process before going to the next step. The second step is aesthetic fitness function to evaluate aesthetics of art forms. A new aesthetic measure is formulated, based on IFS's characteristics, aesthetic theory, and human perception. The experimental results of the study are also included in this paper.

Keywords: aesthetics, evolutionary algorithm, fractal, jewelry design.

1. INTRODUCTION

Design and conventional model-making processes are the bottleneck in jewelry industry [1]. Due to they require creativity, craftsmanship, and time consumption, especially in mass production. Even though several CAD software have been developed to facilitate designers' tasks. Most of jewelry designers, who are unfamiliar to CAD environments, have to spend longer time to draw the details of jewelry than hand-drawing. As a result, a tool that links between CAD and designer is developed, based on AI techniques such as expert system and case-based reasoning [2]. However, the mentioned tool still has limitations in jewelry design database and variety of jewelry designs. It depends on the development of knowledge base. One possible way to solve such limitations is based on evolutionary process. Wannarumon et al. [3] have proposed a new evolutionary design approach to create non-functional art forms for jewelry design. The improvement of such approach and the quantitative aesthetics are presented in this paper.

2. LITERATURE REVIEW

This section principally investigates and discusses in three relevant areas: evolutionary art and design systems including major mechanisms, iterated function system (IFS), and theories of computing aesthetics.

2.1 Evolutionary Art and Design Systems

Evolutionary art and design system is an effective way to create attractive pieces of art, which possess very distinct styles but mostly non-functional. In evolutionary art system, evolution works as a form generator rather than an optimizer, by providing varieties of forms. As a result, designer can explore more design alternatives. During evolutionary process, the fitness functions to judge aesthetics can be done by human evaluator or the developed software. In addition, the evolutionary process should continuously generate the new art forms based on the individuals' fitnesses from the previous generations. There have been several researches in these areas, which are used in design applications including creations of artistic forms [4-8].

Genotypes are genetic representations that codes for generating an individual. Mostly, they are encoded in string of chromosomes as the basic unit of evolution. Suitable structures and representations allow us to easily apply genetic operators. Genotype can be encoded in both binary and real numbers.

In general, genetic operators are crossover and mutation, mostly used is mutation, due to the fixed structure of representation. Thus new offspring are generated by mutating the copies of parents.

Phenotype is applied to represents individual itself and generally consists of sets of parameters to represent shapes or forms. Art forms or phenotypes have been represented with techniques depending on the systems' purposes [4-8].

Fitness function represents a heuristic estimation of solution quality. It is derived from the objective functions, to measure the phenotypes' abilities or properties. It is a key point to appropriately lead the individuals' evolution. Every new phenotype must be evaluated its fitness or a level of goodness for each solution. In evolutionary design, almost all computation time is spent in the evaluation process [4], which can take few minutes until hours to evaluate a single solution. Thus, it would be better to reduce or minimize number of evaluations during evolution process.

Selection is a process to determine the selected phenotypes according to their fitnesses. The selection scheme can enforce the process going on to the divergence or convergence direction.

Most of evolutionary art and design systems generate new forms based on random initial populations. Each individual of population can be evaluated for its fitness by human artist or computer. Often, population size is less than ten individuals [4], which are then judged rapidly in each generation. User-interfaces are typically designed to facilitate user to evaluate individuals' fitnesses, rank or select them to carry on the next process or to terminate system.

2.2 Iterated Function system

Forms of natural creations wonderfully inspire artists and designers to create their elegant and creative art works. Nature has its own geometry; it is nonlinear, complex, and irregular. Such natural forms can be represented by fractals was coined by [9]. He proposed the fractal geometry of nature to represent and to describe the nature phenomena, structures, and objects such as cloud, tree, and leaf. Fractal geometry provides rigorous concepts and practical techniques, which are capable of formulating the mathematical model and analyzing of irregular processes.

Iterated Function Systems (IFS) introduced by [10] are very interesting due to its mathematical soundness and simplicity, and useful for modeling and generating self-similar fractals. Encoding any images by traditional methods consists of a long list of addresses and attributes. In this study, the compact sets of numbers (IFS codes) are feasible to encode in the chromosomes act as genotypes to represent the art forms.

IFS of affine transformations in $\mathbb{R}^2$ can be represented as $\{\mathbb{R}^2; w_1, w_2, \ldots w_N\}$, where w_i are affine transformation in $\mathbb{R}^2$.

The notation of an IFS of affine map can be written as below,

$$w_i(x,y) = w_i\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a_i & b_i \\ c_i & d_i \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} e_i \\ f_i \end{bmatrix} = A_i(x,y) + t_i\,, \tag{1}$$

where $a_i, b_i, c_i, d_i \in [-1,1]$ and $(e_i, f_i) \in \mathbb{R}^2$. Other properties of IFS see [10].

IFS is encoded in a chromosome as illustrated in Fig.1.

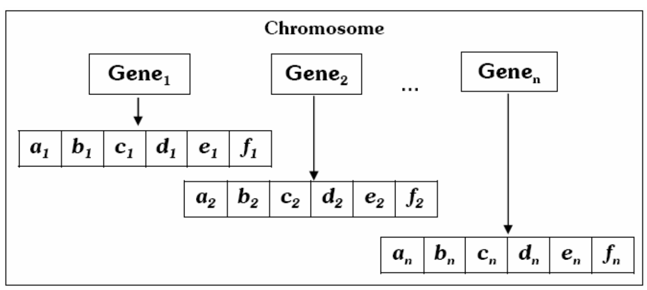


Fig. 1. Genetic representation.

2.3 Computing Aesthetics

Birkhoff [11] introduced the well-known aesthetic measure theory, by analyzing the aesthetic experience. He suggested that 'the aesthetic feeling arise primarily because of an unusual degree of harmonious interaction within the object. Remko and Rens [12] had reviewed several aesthetic measure theories. They suggested that building the formal models of human perceptual processes are the basis of any empirical aesthetic measure. Machado and Cardoso [13] explained that visual aesthetic value is directly related to visual image perception and interpretation. Their formula to evaluate the aesthetic value mainly considers the image complexity. Nimii et al. [14] measure the complexity of an image embedding in the black-and-white image. Golden ratio [15] expresses the appropriate ratio or section of two sub-parts described the good proportion that influence on art and architecture. Weyl [16], Rosen [17] and Field [18] express roles of symmetry that influence aesthetics. Sprott [19] quantifies the aesthetics of chaotic patterns by measuring fractal dimension and Lyapunov exponent. Spehar et al. [20] study the aesthetics of fractals that depends on fractal dimension.

3. AESTHETIC CONSIDERATIONS

Several issues related to aesthetics are summarized to acquire main factors with respect to aesthetic judgment. Here, the characteristics of aesthetics are golden ratio, rotational symmetry, logarithmic spiral symmetry, mirror symmetry, complexity, compactness and connectivity, unpredictability, and fractal dimensions. Such characteristics are quantified based on mathematical foundations of fractal geometry, chaotic behavior and image-processing morphology. Mirror symmetry, rotational symmetry, and logarithmic spiral symmetry are measured using mathematical foundations of fractal geometry, which require IFS codes to estimate those properties. Fractal dimension is quantified in terms of capacity dimension and correlation dimension. Fractal dimension and the largest Lyapunov exponent explain compactness and chaotic behaviors of fractal that require the coordinates of point cloud, which is generated from IFS codes using random iteration algorithm (RIA) [10].

3.1 Capacity Dimension (F_1)

Box-counting or box dimension is used for estimating the capacity dimension D_0 of fractal. The concept of box-counting theorem [10] is subdividing the bounding box of fractal with boxes of side length ($1/2^s$), where s is number of steps, and then counting number of boxes that intersect the fractal. Capacity dimension is the logarithmic rate at which $N_s(F)$ increases as $s \to +\infty$, and estimated by slope of linear model of $\ln(N_s(F))$ versus $\ln(2^s)$.

3.2 Correlation Dimension (F_2)

Correlation dimension of an attractor relates to contraction rate. It can explain the distribution of points contained in fractal. The approach to compute the correlation dimension D_2 introduced by Grassberger and Procaccia [21] is applied to measure D_2 of IFS fractals. D_2 can be computed using the correlation integral function provided in OpenTSTOOL [22]. The correlation dimension D_2 is estimated using the least-squares linear regression of $\log C(r_k)$ versus $\log(r_k)$, then the slope of linear model represents D_2.

3.3 Largest Lyapunov Exponent (F_3)

The largest Lyapunov exponent λ_1 is studied to measure IFS fractals' pattern, because it can explain the entire spectrum of Lyapunov exponents $\lambda_i (i = 1, 2, ..., n)$, and $\lambda_1 \geq \lambda_2 \geq ... \lambda_n$. The largest Lyapunov exponent measures the sensitivity to initial conditions in a dynamical system that indicates chaos. The positive largest Lyapunov exponent λ_1 is quantified based on Sato et al. [23] and Parlitz [24].

3.4 Image Complexity (F_4)

Applying Niimi et al. method [14] to measure complexity of IFS fractal, the image-processing techniques are used for approximating the bounding box of fractal, and transforming the image format to a matrix of 0 and 1. Bounding box is represented by width W_B and length L_B. The total length of black-and-white border of the fractal is calculated by the summation of number of color-changes along rows and columns in the bounding box. The maximum border length is computed from $W_B \times (L_B - 1)) + ((W_B - 1) \times L_B$.

3.5 Golden Ratio (F_5)

Golden rectangle becomes the notion to measure the suitable proportion of width and length of bounding box of IFS fractal in this study. With the assumption, the proportion of bounding box can be used to explain the feature contained inside it. Golden rectangle then is used to be a reference base.

Define the reference axis A is perpendicular to the finger, while the reference axis B is along with finger as illustrated in Fig. 2. Find the centroid of the fractal, and then place the reference axes on it. The reference axes are rotated until obtains the maximum value of golden ratio.

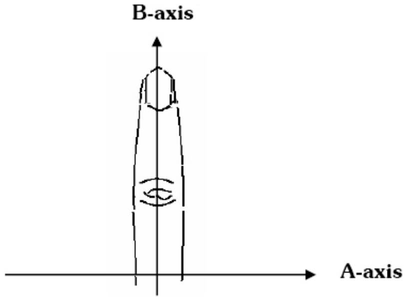


Fig. 2. Reference axes relative to human finger.

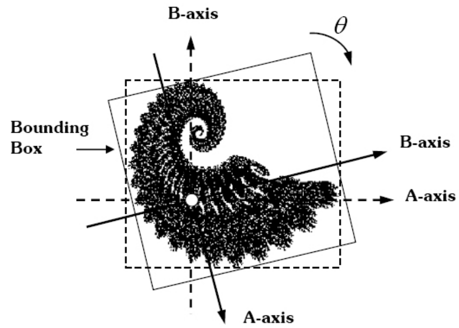


Fig. 3. Measuring golden ratio of IFS fractal.

3.6 Mirror Symmetry (F_6)

Mirror symmetry depends on the reference axes like as golden ratio. It is quantified using image-processing based morphology. We define two reference axes like as shown in Fig. 2. Find the centroid of the fractal, and then place the reference axes on it. Divide the fractal into two parts along *B*-axis. Compute the difference between two parts L_{part} and R_{part}, then rotate the reference axes until obtains the minimum value of ΔM , shown in Fig. 4.

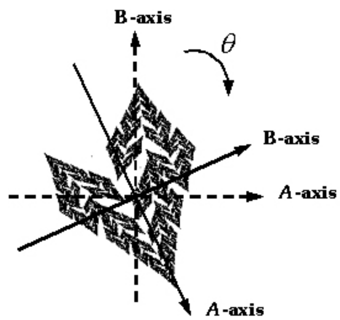


Fig. 4. Rotating the reference axes until obtains the maximum value of mirror symmetry.

3.7 Rotational Symmetry (F_7)

Rotational symmetry of IFS fractal can be measured from similitude explained in [10]. Properties of similitude allow us to use similitude for quantifying the rotational symmetry. To compute rotational symmetry, an affine map can be rewritten in the polar form as

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix} = \begin{pmatrix} r_1 \cos\theta_1 & -r_2 \sin\theta_2 \\ r_1 \sin\theta_1 & r_2 \cos\theta_2 \end{pmatrix}$$

If any affine map holds a rotation, it will appears r and θ . Any IFS art form that has rotational symmetry contains at least one rotational affine map. Thus, the idea of measuring the rotational symmetry of IFS art form begins with checking all affine maps whether appear at least one rotational affine map. The fractal that holds rotational symmetry will have the conditions as follows:

1) $\Delta(\theta_1, \theta_2) \to 0$ and $\Delta(r_1, r_2) \to 0$,
2) $\theta_1, \theta_2 \geq 45°$ and $r_1, r_2 \to 1$

3.8 Logarithmic Spiral Symmetry (F_8)

Like as rotational symmetry, logarithmic spiral symmetry in IFS fractal can be quantified from similitude. Any IFS art form that has rotational symmetry contains at least one rotational affine map. Thus, measuring logarithmic spiral symmetry of IFS art form starts with checking all affine maps whether appear at least one rotational affine map. The process to quantify logarithmic spiral symmetry is similar to rotational symmetry. The fractal that holds logarithmic spiral symmetry will have the conditions as follows:

1) $\Delta(\theta_1, \theta_2) \to 0$ and $\Delta(r_1, r_2) \to 0$,
2) $\theta_1, \theta_2 < 45°$ and $r_1, r_2 \to 1$.

4. FORMULATION OF AESTHETIC MODEL

The quantitative aesthetics is formulated, based on aesthetic considerations in Section 3. This aesthetic measure will be used as the fitness function in the EA. The measure is designed into two steps:

4.1 Morphological Measure

Morphological measure is used to quantify compactness and connectivity of art forms. This measure will work as morphological fitness function in the EA to sort the unqualified art forms, which is incompact, unbounded, and disconnected out of the qualified art forms. Firstly, compactness and connectivity of art forms are quantified using image-processing based morphology [25]. Compactness is computed from perimeter power two divided by area of art form. Connectivity is computed by counting number of the connected pixels. Secondly, we statistically analyze relationships between compactness and connectivity and aesthetic variables in Section 3. It is found that capacity dimension, correlation dimension, and largest Lyapunov exponent have influence on compactness and connectivity. Capacity dimension quantifies a feeling of density, when a fractal fills up the space. Correlation dimension explains the contraction rate of a fractal. Largest Lyapunov exponent can measure the separations of points generating a fractal. Using factor analysis, the linear model of a factor expressed compact and connectivity is

$$fac_{cc} = 0.494D_0^T + 0.494D_2^T + 0.214\lambda_1^T , \tag{2}$$

where D_0^T, D_2^T, and λ_1^T are normalized capacity dimension, correlation dimension, and largest Lyapunov exponent respectively. Using regression analysis, the linear model of compactness and connectivity is

$$\hat{CC} = 4.2184e^{0.3561 fac_{cc}} - 4.9605 , \tag{3}$$

$\hat{CC}$ is compactness and connectivity value, which ranges in [0,1].

4.2 Aesthetic Measure

All aesthetic variables in Section 3 are normalized in range of [0, 1]. Using factor analysis, these aesthetic variables are classified into two main factors:

$$fac_1 = 0.304 \bullet F_1 + 0.234 \bullet F_2 - 0.202 \bullet F_3 + 0.317 \bullet F_4 + 0.186 \bullet F_5 - 0.065 \bullet F_6 + 0.17 \bullet F_7 + 0.06 \bullet F_8, \tag{4}$$

$$fac_2 = 0.103 \bullet F_1 - 0.01 \bullet F_2 + 0.077 \bullet F_3 + 0.19 \bullet F_4 + 0.085 \bullet F_5 - 0.425 \bullet F_6 + 0.428 \bullet F_7 + 0.448 \bullet F_8. \tag{5}$$

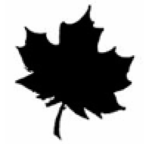
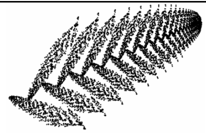
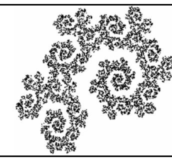
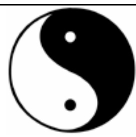
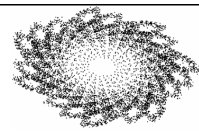
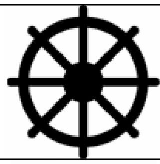
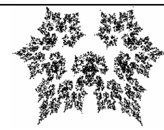
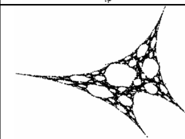
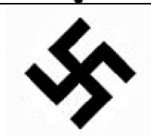
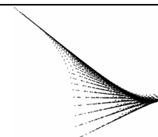
fac_1 mainly explains aesthetics in terms of compactness, connectivity, and complexity of art forms includes mirror symmetry, while fac_2 represents aesthetics as rotational symmetry and logarithmic spiral symmetry.

The quantitative aesthetics is formulated from the survey of human preference on jewelry ring designs. The subjective aesthetic attractiveness of jewelry ring' ornaments is studied under the organized experiment and survey based on theory of design of experiment (DOE). The participants are seventy-two members of the university community. Eighty designs are selected according to difference in their aesthetic variables. The selected designs are randomly arranged to present to participants. After obtain the survey results, we apply statistical analysis and regression technique to formulate the mathematical aesthetics $\hat{S}_a$,

$$\hat{S}_a = -38.8442 + 39.015 \bullet e^{0.0287 \bullet fac_1} - 0.3917 \bullet fac_2 - 0.6526 \bullet fac_2^2 + 0.7553 \bullet fac_2^3. \tag{6}$$

The non-linear model explains that aesthetic value obeys the exponential dependence upon fac_1 and the cubic dependence upon fac_2. Eqn.(6) gives the higher score to the mirror and rotational symmetry as same as the survey results. Most of participants prefer the art forms that present such kinds of symmetry.

Evaluating the aesthetic model by the popular and long-lasting symbols, the results show that such symbols have high aesthetic values. This can prove the aesthetic model.

	Long-Lasting Symbols	Aesthetics $\hat{S}_a$		IFS Fractals	Aesthetics $\hat{S}_a$		IFS Fractals	Aesthetics $\hat{S}_a$
1		0.9121	5		0.8814	9		0.7152
2		0.8912	6		0.8600	10		0.6949
3		0.8680	7		0.8431	11		0.6687
4		0.8448	8		0.8116	12		0.4414

Tab. 1. Examples of evaluating aesthetics using Eqn.(6).

5. A NEW EVOLUTIONARY DESIGN APPROACH

Evolutionary algorithm is applied to outline the approach to create art forms–"jewelry-ring- ornament generator". The system is designed with aims to increase both diversity of art forms and number of alternatives in the design process. The system is based on a multiple parent system rather than single parent and one-couple-parent system. Hence, in the mating stage, the several couples of parents are uniform randomly forming pairs to generate a new batch of offspring simultaneously. The followings describe how the proposed evolutionary-based system works.

STEP 1: Evolutionary process initializes by uniform-randomly selecting a set of individuals in the IFS chromosome library.
STEP 2: Apply the mutation operator to the individuals following to the mutation probability and then fill all individuals and their mutated versions to the population.
STEP 3: Apply the crossover operator to the population regarding to the crossover probability, to produce a new batch of offspring. Then add them to the population.
STEP 4: In mapping process, map the individuals (genotypes) which are now in forms of chromosome strings of IFS codes to fractals (phenotypes).
STEP 5: Go to the first evaluation—"Morphological Fitness Function". Evaluate all individuals for their morphologies. Screen incompact and disconnected art forms out of process.
STEP 6: Select the individuals considering their morphological fitness, which explain their compactness and connectivity.
STEP 7: Go to the second evaluation—"Aesthetic Fitness Function". The survival individuals are evaluated for their aesthetic fitnesses.
STEP 9: Select a set of the best individuals regarding to their aesthetic fitnesses. The number of selected individuals depends on population size, which is explained later in the next section.
STEP 10: Repeat STEP 2 to STEP 9 until the system achieves the termination criteria.

5.1 Genetic Control Parameters

In the proposed EA, three genetic control parameters are mutation probability (p_m), crossover probability (p_c), and population size (*pop_size*). Population size depends on the number of initial parents (n_{ip}), mutation probability (p_m), and crossover probability (p_c). Number of initial parents (n_{ip}) multiplies by mutation probability (p_m) that is

$$round(n_{ip} * p_m)\ . \tag{7}$$

Then the result shows the number of the mutated individuals. We now have total number of individuals (or chromosomes) $n_{ip} + round(n_{ip} * p_m)$. Next, compute the number of pairs for crossover operation by $round\left(\frac{n_{ip} + round(n_{ip} * p_m)}{2} * p_c\right)$. This number of pairs multiplies by 2, that is $2 * round\left(\frac{n_{ip} + round(n_{ip} * p_m)}{2} * p_c\right)$.

It gives the number of new offspring from crossover. Add this number to the total parents in Eqn. (7). Then we obtain the population size (*pop_size*)

$$pop\_size = n_{ip} + round(n_{ip} * p_m) + 2 * round\left(\frac{n_{ip} + round(n_{ip} * p_m)}{2} * p_c\right). \tag{8}$$

5.2 Mapping IFS Genotype to Fractal Phenotype

IFS genotype is mapped to fractal phenotype by using random iteration algorithm (RIA). Barnsley [10] introduces computing probabilities of each affine map in Eqn. (1) as

$$p_i = \frac{|a_i d_i - b_i c_i|}{\sum_{i=1}^{N} |a_i d_i - b_i c_i|}, \qquad \text{for } i = 1, 2, \ldots n \tag{9}$$

where n is number of affine maps. We propose to use uniform random probabilities in RIA to compute fractals. This can increase variety of fractals generated by the EA.

$$p_i \in \cup(0,1) \tag{10}$$

For both cases, computing under the conditions $\sum_{i=1}^{n} p_i = 1$ and $0 < p_i < 1$.

5.3 Genetic Operators

In the EA, we develop two genetic operators to create the new individuals, which offer the variation of both genotypes and phenotypes, based on the existing individuals. The one-dimensional chromosome allows us to easily apply crosser and mutation in the EA.

5.3.1 Multi-Gaussian Mutation

This mutation operator applies Gaussian random numbers to all of the elements in the chromosome, simultaneously. In the other word, it is applied to the whole solution vector rather than a single element, causing the whole vector to be slipped in the space. The element of new individual $O(j)$ is

$$O(j) = E(j) + r_i(0, \sigma_i) \tag{11}$$

where $E(j)$ is element in the existing individual, and r_i is Gaussian random number.

5.3.2 Modified Arithmetic Crossover

The modified arithmetic crossover is a single-point crossover, which generates offspring as the component-wise linear combinations of the parents. The new offspring is

$$\begin{aligned} O_1 &= k_1 \bullet P_1 + (1 - k_2) \bullet P_2 \\ O_2 &= k_2 \bullet P_2 + (1 - k_1) \bullet P_1 \end{aligned} \tag{12}$$

where P_1 and P_2 are chromosomes of two parents, O_1 and O_2 are chromosomes of two new offspring, and k_1, k_2 are the proportions of the inherited gene of P_1 and P_2, respectively. k_1, k_2 determines the crossover point, where the part of chromosome that consists of at least one gene (affine map). The crossover point is not allowed to locate inside the intervals of gene. The crossover point is positioned only where the individuals can exchange genes. The parameter k_1 and k_2 are uniform randomly selected from their possible set of crossover.

5.4 Evaluation Process

The evaluation process is divided into two steps:

5.4.1 Evaluation using Morphological Fitness Function

In this study, any individual that is incompact and disconnected always yields low aesthetics. Therefore, the morphological fitness function in Eqn. (3) is used to screen such individual out of the process before launch to the aesthetic fitness function. This concept can reduce time in process. The individuals (art forms) that have $\hat{CC}$ higher than 0.38 will be selected to go to the next step.

5.4.2 Evaluation using Aesthetic Fitness Function

Art forms that are selected by the morphological fitness function will be evaluated their aesthetics. We use Eqn. (6) to quantify aesthetics of art forms in the process. We use linear rank-based selection to select the individuals to new generation. As well as, we add elitist strategy [26] to our selection scheme. Then all of parents are allowed to undergo selection with their offspring. Elitist strategy can preserve and convey some good individuals or chromosomes to the next consecutive generations. This can protect occurrence of the phenomenon that some good individuals disappear after some generations. This selection is to select a batch of individuals after aesthetic evaluation for new generation.

6. EXPERIMENTAL RESULTS AND DISCUSSIONS

We construct an IFS chromosome library that contains 200 various chromosomes for using in the initial population. The number of initial parents are 2, 3, and 4, when cooperates with mutation and crossover probabilities cause the population size ranges from 3 – 16. The genetic parameters are determined through a set of preliminary experiments as follows:

- Number of initial parents: n_{ip} = 3, mutation probability: p_m = 0.75, crossover probability: p_c = 0.25, following Eqn. (18), population size: *pop_size* = 7.

Unlike the EAs for numerical computation, EA for design deals with graphic system and image processing techniques. Then it relatively consumes a large amount of time in each generation, which regards to the population size. The termination criteria used in the system is the pre-specified maximum number of generations. We study the tested set in long run and find the convergence of aesthetic value. We found that the average of number of generations that aesthetic values converge to the single value equals to 15, as shown in Fig. 8, it take around 1,830 seconds, in average.

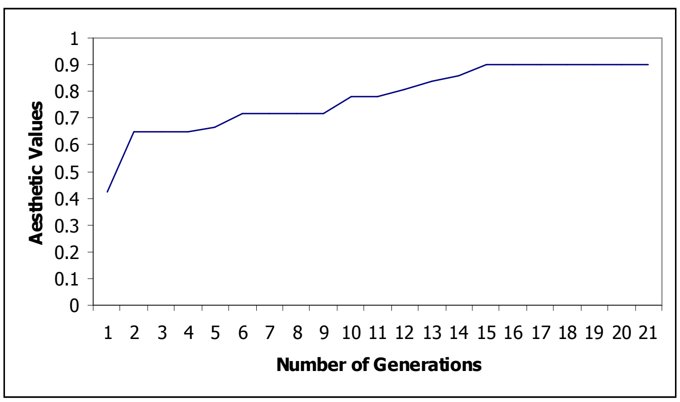


Fig. 8. Convergence of aesthetic value: the predefined maximum number of generations.

To explore the role of probabilities in RIA, we have designed two experiments:

Case 1: Using IFS with the associated probabilities computed from Barnsley's equation in Eqn. (9),

Case 2: Using IFS with the uniform random probabilities in Eqn. (10).

All experiments are implemented on a PC, ACER Pentium 4 (2.8 GHz CPU, 60GB RAM), using MATLAB version 6.5. Due to the output from EA is stochastic; we replicate each test problem 30 times, and then compute the average value for evaluation. From the experimental results, most of aesthetic values deviate from the optimum values as less as lower than 10%, this effect is acceptable for heuristic algorithm, which works with several random numbers. Case 1 yields higher aesthetic fitness within the pre-defined maximum number of generations *(max_gen*=15) than Case 2. Since Case 1 confirms the regular distribution of points through the space of individual (fractal). As a result, most of individuals generated using Case 1 have higher morphological fitnesses than Case 2. Number of selected individuals from the morphological fitness function N_c is also larger than Case 2. Since run time is proportional to population size. Each experiment of Case 1 spent approximately 1,830 sec., while case 2 spent around 1,110 sec. Case 1 then takes longer run time 65% comparing to Case 2.

From Fig. 9, the EA for Case 1 converges to the maximum fitness value since the 7th generation, faster than Case 2. The EA for Case 2 regularly improves the fitness value, and it still not converges to the maximum value. It indicates that when it takes longer time, it can improve the fitness value. Then we should explore more in long run behaviors of Case1 and Case 2. However, one advantage achieved by the second method is that it offers higher variety of forms, and in variety offers creativity. Notice that Case 2 has higher deviation of aesthetic values and run time, and higher improvement ratio. This implies that Case 2 is less consistent than Case 1, because it has more random numbers used in process, but it provides more emergent property to produce the unpredictable forms.

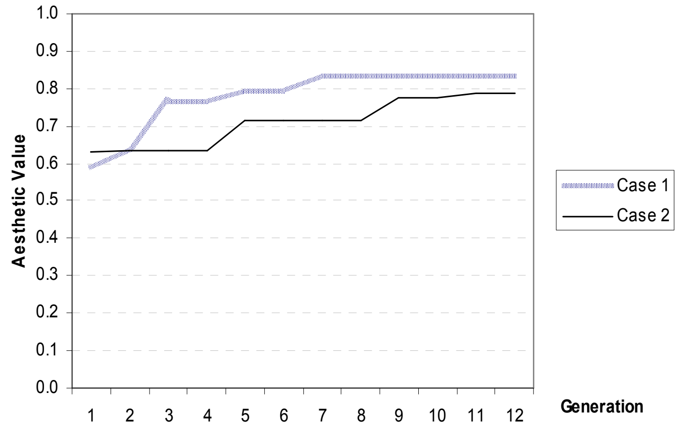


Fig. 9. Behavior of the EA for Case 1 and Case 2.

7. CONCLUSIONS

This paper proposes two issues. First, a new mathematical model of aesthetic measure is formulated by considering theory of aesthetics, IFS fractal's characteristics and human perception on aesthetics. The quantitative aesthetic model is used as fitness function in the EA. Second, a new EA is hybrid between EP, ES, GA and GP according to their special characteristics and advantages. It aims to work as a form generator rather than optimizer. It can offer diversity of designs. It basically starts by initialization of a set of individuals (art forms) by the user. The process generates a new set of art forms based on the existing ones by using genetic operators: multi-Gaussian mutation, and modified arithmetic crossover, which offer variation of the solutions. Art forms are evaluated for their aesthetic values by morphological and aesthetic fitness functions. The process continuously generates a new set of art forms based on the art forms' aesthetic values from the previous generations. This process repeats until reach to a pre-determined maximum number of generations. The approach can increase productivity of jewelry ring design around 80% comparing to traditional design. This approach can be developed for an electronic catalogue to create the jewelry design. Not only jewelry design, the proposed approach is certainly practical for other non-functional designs such as ornamental parts of watches, giftware, car, architecture and furniture, etc. Most of ornamental parts are non-functional, but very important, because they strongly influence human's emotion and product's attractiveness. They essentially specify concepts, images and styles of products. Such attributes can be expressed via forms, curves, lines, symbols, and logos.

8. ACKNOWLEDGEMENT

The author would like to appreciate and thank to her PhD scholarship donor, Austrian Government, include Prof. Dentcho N. Batanov, Asian Institute of Technology, and Dr. Kittinan Unnanon, National Science and Technology Development Agency, Thailand, her PhD thesis committees for their insights, a lot of valuable guidance, and constructive feedbacks, which have contributed to improvements of this research. The author would like to thank CIFAC Jewelry Company, Bangkok, Thailand, for their supporting the useful and valuable information of jewelry design and manufacturing.

9. REFERENCES

[1] Wannarumon, S., and Bohez, E. L. J, Rapid Prototyping and Tooling Technology in Jewelry CAD, *Computer-Aided Design & Applications*, Vol. 1, Nos. 1-4, 2004, pp 569-575.

[2] Wannarumon, S., Unnanon K. and Bohez, E. L. J, Intelligent Computer System for Jewelry Design Support, *Computer-Aided Design & Applications*, Vol. 1, Nos. 1-4, 2004, pp 551-558.
[3] Wannarumon, S., Bohez, E.L.J. and Annanon K., Evolving Jewelry Design based on IFS Fractals and Condensation Sets, in Proceeding of 18th International Conference on Production Research, Italy, 2005.
[4] Bentley, P., *Evolutionary design by computers*, Morgan Kaufmann Publishers, San Francisco, U.S.A, 1999.
[5] Dawkins, R, *The Blind Watchmaker*, Penguin Books, UK, 1986.
[6] Sims, K., Artificial evolution for computer graphics, *Computer Graphics*, Vol. 25, No. 4, 1991, pp 319-328.
[7] Todd, S., and Latham, W., *Evolutionary Art and Computers*, Academic Press, London, 1992.
[8] Gero, J., Creativity, emergence and evolution in design: concepts and framework, *Knowledge-Based Systems*, Vol. 9, No. 7, 1996, pp 435-448.
[9] Mandelbrot, B., *The Fractal Geometry of Nature*, 3rd Ed, W.H.Freeman, 1982.
[10] Barnsley, M., *Fractal everywhere*, 2nd Ed., Academic Press. San Diego, U.S.A, 1993.
[11] Birkhoff, G., *Aesthetic Measure*, Harvard University Press, UK, 1933.
[12] Remko, S., and Rens, B., Computational Esthetics (English translation of "Computationele Esthetica", originally published in Dutch in *Informatie en Informatiebeleid*, Vol. 11, No. 1, 1993, pp 54-63.
[13] Machado, P., and Cardoso, A., Computing aesthetics. In: Oliveira, F. (Ed.), *Procs. XIVth Brazilian Symposium on Artificial Intelligence SBIA'98*, Porto Alegre, Brazil, LNAI Series, 1998, pp 219-229.
[14] Niimi, M., Noda, H., and Kawaguch, E., An image embedding in image by a complexity based region segmentation method, in *Int. Conf. on Image Processing* (*ICIP'97*), Vol. 3. 1997, pp 1026-1030.
[15] Huntley, H. E, *The Divine Proportion*, Dover, New York, 1970.
[16] Weyl, H., *Symmetry*, Princeton University Press, New Jersey, U.S.A, 1952.
[17] Rosen, J., *Symmetry Discovered: Concepts and Applications in Nature and Science*, 2nd Ed, Dover Publications, 1998.
[18] Field, M., Designer Chaos, *Computer-Aided Design*, Vol. 33, 2001, pp 349-365.
[19] Sprott, J. C., Quantifying Aesthetic Preference for Chaotic Patterns, *Empirical Studies of The Arts*, *J. Int. Assoc. of Empirical Aesthetic*, Vol. 14, No. 1, 1996, pp 1-16.
[20] Spehar, B., Clifford, C. W. G., Newell, B. R. and Taylor, R. P., Universal Aesthetic of Fractals, *Computer & Graphics*, Vol. 27, 2003, pp 813-820.
[21] Grassberger, P., and Procaccia, I., Measuring the strangeness of strange attractors, *Physica D*, 9, 1983, pp 189-208.
[22] Merkwirth, C., Parlitz, U., Wedekind, I., and Lauterborn, W., *OpenTSTOOL*, MatLAB toolbox, 2002. http://www.phsik3.gwdg.de/tstool/
[23] Sato, S., Sano, M., and Sawada, Y., Practical methods of measuring the generalized dimension and the largest Lyapunov exponent in high dimensional chaotic systems, *Prog.Theor. Phys*. Vol. 77, 1987.
[24] Parlitz, U., Nonlinear Time-Series Analysis, in *Nonlinear Modeling- Advanced Black-Box Techniques*, Suykens, J.A.K., and Vandewalle, J.Eds, Kluwer Academic Publishers, 1998, pp 209–239.
[25] Gonzalez, R., and Woods, R., *Digital Image Processing*, 2nd Ed, Prentice Hall, 2001, pp 568-572.
[26] Bäck, T., and Hoffmeister, F., Extended Selection Mechanisms in Genetic Algorithms', in *Proceeding of the Fourth International Conference on Genetic Algorithms*, Belew, R. and Booker, L. (Eds.), Morgan Kaufmann Publishers, San Mateo, CA, 1991.