Empirical Evaluation of Mutation Step Size in Automated Evolution of Non-Target-Based 3D Printable Objects

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Abstract— Evolutionary algorithms (EA) currently play a central role in solving complex, highly non-linear problems such as in engineering design, computational optimization, bioinformatics and many more diverse fields. Implementation of EAs in the field of 3D printing is still in its infancy since 3D printing itself is a relatively new technology that has only become main stream due to its significant decrease in acquisition cost in the past 2-3 years. Due to the rapid uptake by everyday hobbyists and the significant advancements being made in material diversity, 3D printing will only continue its rapid expansion into our everyday lives. In this study, an EA in the form of Evolutionary Programming (EP) is used to automatically evolve 3D objects generated by Geilis's Superformula. The focus of this study is to explore the mutation step size in hoping to create more diverse populations in the evolution of the generated 3D printable objects. In EP, the operator responsible for offspring generation is through the mutation process solely. Hence, the mutation step size has a direct and very significant impact on the diversity of the offspring generated. A fitness function was design to evaluate the 3D objects and shapes generated by the Superformula. The parameters for the Superformula to generate 3D objects or shapes are m_1, m_2, $n_{1,1}$, $n_{1,2}$, $n_{1,3}$, $n_{2,1}$, $n_{2,2}$, and $n_{2,3}$. These parameters serve as a representation in EP and the mutation step size will affect the chances of these parameters' values to change. To carry out this study, five different mutation step sizes were used and each mutation step size will be run for five times. The mutation step sizes are 0.1, 0.2, 0.4, 0.6 And 0.8. From the results obtained, a mutation step size 0.1 shows a more stable population pool and were able to generate diverse and distinctive 3D objects.

Keywords— Automatic 3D shape evolution, Evolutionary art, Gielis Superformula, Evolutionary Programming (EP), Evolutionary Algorithm (EA), 3D printing, mutation step size

I. INTRODUCTION

3D printing machines are able to make prints of 3D objects at a relatively low cost in very small quantities [12] even at the convenience of your own home. However, designing the 3D shapes is not an easy task; skills and experience on using 3D-object design software is crucial in the 3D objects and shapes design process. It requires a great amount of time to complete the design of a complex 3D object even by a CAD professional. Numerous researchers have since taken up the challenge to attempt 2D and 3D objects generation through computational methods. Some of the early studies done on geometrical modelling evolution in a 3D space are exploration of the lattice deformation [2] by Watabe and Okino and polygonal sequencing operators [1] by McGuire. Further works and studies were carried out by using different encoding such as the work by Sims [3] using directed graph encoding in morphology and behavior evolution of virtual creatures in a 3D environment. The usage of L-system encodings was explored by Jacob and Hushlak [4] to create virtual sculptures and furniture designs. Exploration of evolutionary variable and fixed length direct encoding on solid objects such as tables, cars, boat and even a the layout of a hospital department [5].

The Superquadrics equation in representing geometric shapes was introduced by Barr. It has been used as quantitative models for diverse applications in computer environments [6,7] such as computer graphics as well as in computer vision [8]. Since then, Superquadrics has been extended in local and global deformations to be able to model natural and considerable precision of synthetic shapes.

Geilis's Superformula, generalized from Superellipses and the Superquadric formula, was able to describe shapes through its internal symmetry and internal metrics [9]. The Superformula equation is then further used to represent shapes in various fields such as engineering [10] and it has been used together with EA to achieve a certain target shapes [11].

EAs are inspired by natural selection of the fittest and it has been used as an optimization technique to solve engineering, mathematical, computational and many more complex problems. EAs main genetic operators comprise population, parent, recombination, mutation, offspring, and survivor selection. It has four different classes, which are Genetic Algorithms, Evolutionary Programming (EP), Evolution Strategies (ES), and Genetic programming [14]. Each class utilizes different approaches in solving complex problem while maintaining the main genetic operators.

In this paper, we explore the effect of mutation when using the Superformula to create non-target based 3D shapes through EP. The focus of this study is to investigate the favourable mutation step sizes for mutating the parameter encoding's values that are used in the Superformula in order to automatically generate 3D shapes and object through EP. By empirically testing the different mutation step sizes of the parameter values, the diversity of the search space for novel and unique 3D objects and shapes can increase.

This paper is divided into a few sections. The following section of this paper will discuss the background of the Superformula and how it is able to generate 3D shapes from generalizing the Superellipses and Superquadric equations. It will be followed by another section on the flow of Evolutionary Programming. The experimental setup section will be presented next and followed by the results section. The last section will be the conclusion and future work.

II. METHOD

A. Superformula

The Superformula is simple geometric equation formed from the generalisation of a hyper-ellipse. It was found to be able to model forms of a large variety of plants and other living organisms [13]. The generalization of the Superellipse equation is as follows:

$$r(\theta) = \frac{1}{\sqrt[n_1]{\left[\left(\left|\frac{1}{a} \cdot \cos\left(\frac{m}{4} \cdot \theta\right)\right|\right)^{n_2}\right] + \left[\left(\left|\frac{1}{b} \cdot \sin\left(\frac{m}{4} \cdot \theta\right)\right|\right)^{n_3}\right]}} \quad (1)$$

The distance in polar coordinates is denoted by r, for n_i and m$\in R^+$; a, b$\in R_0^+$; a > 0, b > 0 are responsible for the size of the supershapes with the usual value being set to one. The symmetry number is controlled by m while the shape coefficients are controlled by n1, n2 and n3 with real valued parameters. E (1) forms the superellipse 2D shapes, henceby multiplying 2 superellipse equations together, it allows the extension towards 3D shapes:

$$x = r_1(\theta) \cdot \cos\theta \cdot r_2(\varphi) \cdot \cos(\varphi) \quad (2)$$
$$y = r_1(\theta) \cdot \sin(\theta) \cdot r_2(\varphi) \cdot \cos(\varphi) \quad (3)$$
$$z = r_2(\varphi) \cdot \sin(\varphi) \quad (4)$$

θ, denotes longitude with $-\pi \le \theta \le \pi$ and φ, denotes latitude with $-\frac{\pi}{2} \le \varphi \le \frac{\pi}{2}$

As such, more complex 3D shapes can be generated. Preen [10] has shown more complex shapes such as the Mobius strip, shell and even torus shapes can be generated with the Superformula.

B. Evolutionary Programming

Evolutionary Programming (EP) serves as the EA method in this study. EP is one of the four major EA methods. It was first introduced by Fogel [15] to simulate learning processing aiming to generate artificial intelligence. Adaptive behavior is the key to EP and by using real-value parameters it can be integrated to the problem domain. The real-value parameters of Superformula are used as the representation in EP for this study.

Below is the pseudocode for EP in this study:
1. Generate initial population
2. Test each individual solution in the population
3. Parent selection
4. Mutation process
5. Offspring generation
6. Repeat step 2 to 5 until reach termination criteria

C. Evaluation Function

Evaluation Function serves as a representation of requirement for a solution to adapt to. It is the basis of selection to aid improvements of the individual solution. From the perspective of problem-solving, it is the representation to the task to be solved in evolutionary background [14]. Basically it serves as a quality measurement of the individual solution presented in the population pool. In this study, the evaluation function is design to calculate the value obtain from the 3D object as well as from the Superformula.

$$\frac{\left(\left(200000 - \hat{V}\right) + \sigma_x + \sigma_y + \sigma_z\right)^{-\sqrt{\left(n_{2,2} - n_{2,3}\right)^2}}}{m_1 + m_2 + 1} \quad (5)$$

In equation (5), it was intended to find the spread of points x, y, and z over the symmetry number of any given object. A penalty will be imposed to the score if the dimension of the objects become too big and going out of the boundary set. The reason for the penalty imposed is to maintain a reasonable dimension size. The value for m_1 and m_2 are responsible for the symmetry of the 3D object, both the value of m_1 and m_2 are added together with a constant of 1. The constant is used to counter the division by zero error in the case where the addition between m_1 and m_2 results in zero. Another penalty is imposed by using the power to the difference of $n_{2,2}$ and $n_{2,3}$. In the Superformula, the values of $n_{2,2}$ and $n_{2,3}$ are to control the thickness of each of the layers generated and with this penalty, thin layers or structures to the 3D objects can be avoided and printed out successfully without deformation.

III. EXPERIMENTAL SETUP

The population size model used is the μ+λ method with both parameters set to a size of 1 and 100 respectively which means the population size model will include the parent plus 100 offspring. Each individual in the population pool will be evaluated using the fitness function in equation (5) and hence the fittest individuals will be selected to seed the next generations. There will be five different sets of mutation step size of 0.1, 0.2, 0.4, 0.6, and 0.8 where each mutation step size will be run five times and the final objects of each runs were printed out and analyzed visually. The number of generations set for this experiment is 10. Object evolved are first saved into an Autocad file format (.dxf) and later converted into a STereoLithography (.stl) format. With the .stl format, the object isthen uploaded into the UP! Print preview as shown in Fig 1.
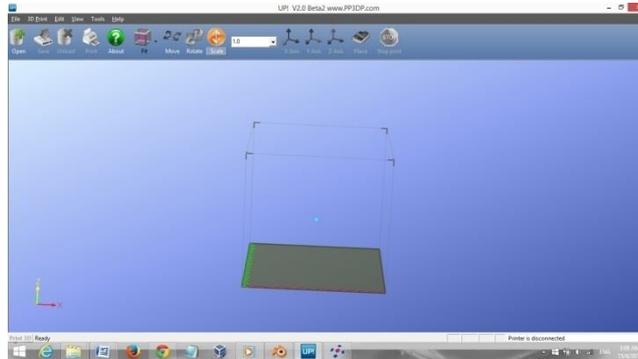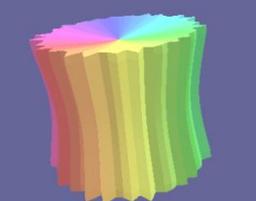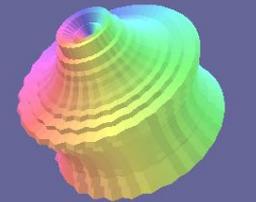

Fig. 1 UP! 3D Printer interface

IV. EXPERIMENT RESULTS

TABLE I

RESULTS OBTAIN FROM MUTATION STEP SIZE 0.1

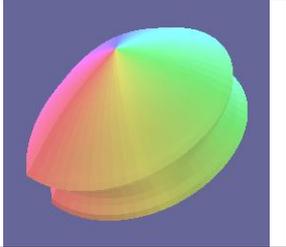| Run	Parameters	Evolved 3D object
1	$m_1 = 23$, $m_2 = 44$, $n_{1,1} = 79.8$, $n_{1,2} = 50.4$, $n_{1,3} = 83.2$, $n_{2,1} = 14.3$, $n_{2,2} = 57.2$, $n_{2,3} = 70.5$	
2	$m_1 = 25$, $m_2 = 4$, $n_{1,1} = 111.2$, $n_{1,2} = 98.2$, $n_{1,3} = 56.6$, $n_{2,1} = 67.1$, $n_{2,2} = 93.4$, $n_{2,3} = 91.3$	
3	$m_1 = 53$, $m_2 = 120$, $n_{1,1} = 24.2$, $n_{1,2} = 44.4$, $n_{1,3} = 21.5$, $n_{2,1} = 63.6$, $n_{2,2} = 0.3$, $n_{2,3} = 90.2$	
4	$m_1 = 61$, $m_2 = 113$, $n_{1,1} = 107.8$, $n_{1,2} = 26.1$, $n_{1,3} = 47.2$, $n_{2,1} = 90.5$, $n_{2,2} = 93.7$, $n_{2,3} = 59.4$	
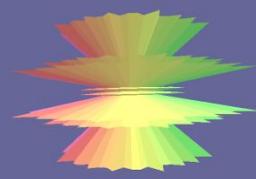
5	m_1 =119 , m_2=6 , $n_{1,1}$=33.2, $n_{1,2}$ =37.1, $n_{1,3}$ =83.4, $n_{2,1}$=28.9, $n_{2,2}$=96.5, $n_{2,3}$=6.2	

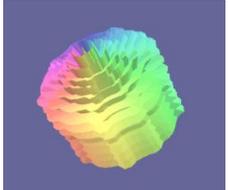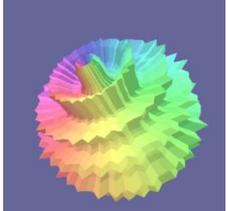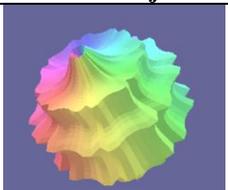TABLE III
RESULTS OBTAIN FROM MUTATION STEP SIZE 0.2

| Run	Parameters	Evolved 3D object
1	m_1 =74, m_2=78 , $n_{1,1}$=77.4 , $n_{1,2}$ =12.8 , $n_{1,3}$ =47.8 , $n_{2,1}$=75.8 , $n_{2,2}$=89.0 , $n_{2,3}$=76.3	
2	m_1 = 67, m_2=58 , $n_{1,1}$=9.4 , $n_{1,2}$ =110.6 , $n_{1,3}$ =42.1 , $n_{2,1}$=7.4 , $n_{2,2}$=117.2 , $n_{2,3}$=0.5	
3	m_1 =76, m_2=3 , $n_{1,1}$=1.4 , $n_{1,2}$ =103.2 , $n_{1,3}$ =86.6 , $n_{2,1}$=116.0 , $n_{2,2}$=40.1, $n_{2,3}$=30.6	
4	m_1 =61, m_2=501 , $n_{1,1}$=29.0 , $n_{1,2}$ =39.3 , $n_{1,3}$ =111.7 , $n_{2,1}$=6.3, $n_{2,2}$=72.4, $n_{2,3}$=81.9	
5	m_1 =27, m_2=105 , $n_{1,1}$=77.7 , $n_{1,2}$ =49.1 , $n_{1,3}$ =26.4 , $n_{2,1}$=55.9 , $n_{2,2}$=93.5 , $n_{2,3}$=63.2	

TABLE IIIII
RESULTS OBTAIN FROM MUTATION STEP SIZE 0.4

Run	Parameters	Evolved 3D object
1	m_1 =75, m_2=11 , $n_{1,1}$=81.7 , $n_{1,2}$ =111.9 , $n_{1,3}$ =21.0 , $n_{2,1}$=62.0 , $n_{2,2}$=33.1 , $n_{2,3}$=62.4	
2	m_1 = 30, m_2=64 , $n_{1,1}$=5.4 , $n_{1,2}$ =3.2 , $n_{1,3}$ =6.5 , $n_{2,1}$=25.1 , $n_{2,2}$=62.2, $n_{2,3}$=38.5	
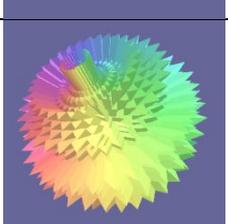
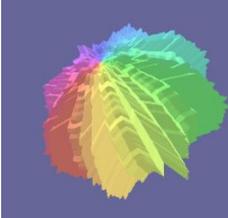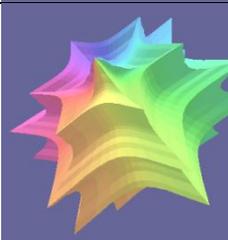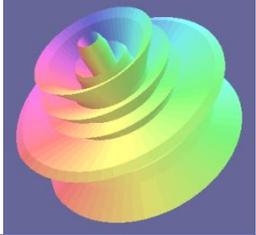| 3	$m_1 = 83$, $m_2=24$, $n_{1,1}=20.3$, $n_{1,2}=114.2$, $n_{1,3}=110.9$, $n_{2,1}=73.3$, $n_{2,2}=35.8$, $n_{2,3}=68.7$	
4	$m_1 = 110$, $m_2=114$, $n_{1,1}=20.8$, $n_{1,2} =3.4$, $n_{1,3} =116.9$, $n_{2,1}=70.3$, $n_{2,2}=3.7$, $n_{2,3}=15.2$	
5	$m_1 =77$, $m_2=42$, $n_{1,1}=1.6$, $n_{1,2} =80.7$, $n_{1,3} =67.9$, $n_{2,1}=5.7$, $n_{2,2}=103.0$, $n_{2,3}=25.1$	
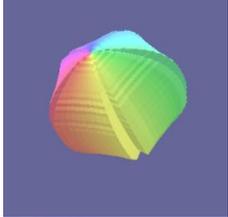
TABLE IVV
RESULTS OBTAIN FROM MUTATION STEP SIZE 0.6

Run	Parameters	Evolved 3D object
1	$m_1 =86$, $m_2=73$, $n_{1,1}=73.5$, $n_{1,2} =106.2$, $n_{1,3} =112.4$, $n_{2,1}=74.4$, $n_{2,2}=5.3$, $n_{2,3}=86.6$	
2	$m_1 =66$, $m_2=110$, $n_{1,1}=66.0$, $n_{1,2} =104.5$, $n_{1,3} =101.5$, $n_{2,1}=84.6$, $n_{2,2}=80.7$, $n_{2,3}=95.4$	
3	$m_1 =25$, $m_2=85$, $n_{1,1}=3.0$, $n_{1,2} =76.6$, $n_{1,3} =102.3$, $n_{2,1}=80.6$, $n_{2,2}=67.4$, $n_{2,3}=77.8$	
4	$m_1 =21$, $m_2=51$, $n_{1,1}=106.0$, $n_{1,2} =85.1$, $n_{1,3} =94.6$, $n_{2,1}=2.5$, $n_{2,2}=40.6$, $n_{2,3}=8.4$	
5	$m_1 =17$, $m_2=63$, $n_{1,1}=92.9$, $n_{1,2} =73.0$, $n_{1,3} =105.0$, $n_{2,1}=8.5$, $n_{2,2}=7.7$, $n_{2,3}=115.2$	
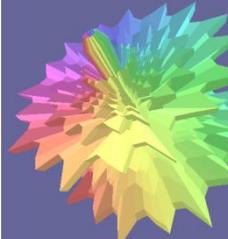
TABLE V
RESULTS OBTAIN FROM MUTATION STEP SIZE 0.8

Run	Parameters	Evolved 3D object
1	$m_1 = 1$, $m_2 = 92$, $n_{1,1} = 45.2$, $n_{1,2} = 9.2$, $n_{1,3} = 107.2$, $n_{2,1} = 24.1$, $n_{2,2} = 28.8$, $n_{2,3} = 76.3$	
2	$m_1 = 119$, $m_2 = 105$, $n_{1,1} = 105.2$, $n_{1,2} = 105.8$, $n_{1,3} = 60.4$, $n_{2,1} = 18.0$, $n_{2,2} = 61.5$, $n_{2,3} = 103.3$	
3	$m_1 = 8$, $m_2 = 58$, $n_{1,1} = 56.4$, $n_{1,2} = 46.5$, $n_{1,3} = 90.9$, $n_{2,1} = 64.2$, $n_{2,2} = 7.0$, $n_{2,3} = 83.5$	
4	$m_1 = 42$, $m_2 = 22$, $n_{1,1} = 62.8$, $n_{1,2} = 107.7$, $n_{1,3} = 112.4$, $n_{2,1} = 23.7$, $n_{2,2} = 7.4$, $n_{2,3} = 90.2$	
5	$m_1 = 1$, $m_2 = 110$, $n_{1,1} = 57.4$, $n_{1,2} = 61.3$, $n_{1,3} = 9.2$, $n_{2,1} = 19.8$, $n_{2,2} = 87.9$, $n_{2,3} = 31.5$	
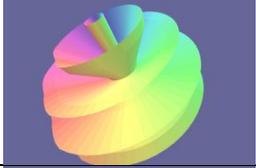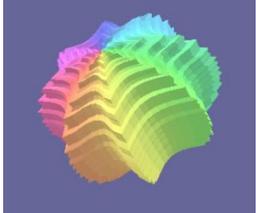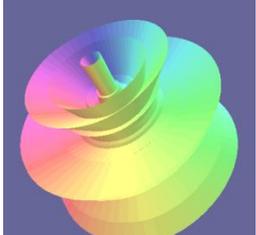
From the results obtained, a mutation step size 0.1 showed a more steady generation of offspring. Since the chances of mutating from the parents are lowest, hence most of the traits from the parents were retained. From Table I, the final objects from the mutation step size 0.1 shows more distinction from each other. Runs no.3 and no.5 generated objects that were unique and both the objects were printed out and shown in Fig 2 and Fig 3 respectively.

Fig. 2 The final object from run no. 3 mutation step size 0.1

Fig. 3 The final object from run no. 5 mutation step size 0.1

Table II shows the results obtained from mutation step size 0.2. Observing the final objects in Table II, only one out of five objects looks unique which is run no.2 and it was printed out and shown in Fig 4. Objects from run no.3 and no.4 looks distorted and attempts to print them out were not successful due to the dispersion of the objects' structure while the remaining two objects look almost similar and very spiky around the edges.

Fig. 4 The final object from run no. 3 mutation step size 0.2

The evolved objects from mutation step size of 0.4 for all five runs are shown in Table III. From Table III, only objects from run no.1 and no.4 looked somewhat unique while the other three again looked similar being round and spiky at the edges. The final objects from run no.1 and no.4 were printed out and shown in Fig 5 and 6 respectively.

Fig. 5 The final object from run no. 1 mutation step size 0.4

Fig. 6 The final object from run no. 4 mutation step size 0.4

Fig. 7 The final object from run no. 4 mutation step size 0.6

Results from mutation step size 0.6 showed an even more spiky shape being generated but run no. 4 produced quite a unique shape which had numerous but very small spiky edges. The final object from run no. 4 was printed out and shown in Fig 7. Mutation step size 0.8 did not evolve favourable results as most of the final objects were either too spiky or simply very plain, uniformly rounded shapes. From all the results obtained, it was deduced that increasing the mutation step size beyond 0.1 will not produce promising results. The occurrence of these results may be due to the existence of many bad regions in the search space and with increased mutation rates, the probability of falling into these bad region increases.

V. CONCLUSION AND FUTURE WORK

From this study, the favourable mutation step size for the parameter value of the Superformula was investigated. Obtaining these mutation step size values will be informative to serve as a reference point for future studies on the Superformula for automated 3D object and shape evolution. These findings will assist future researchers to avoid falling into the undesirable regions of the parameter search space.

Future work should be focused on performing more parameter optimization for the Superformula so that it can also optimally generate shapes such as Mobius strip, toruses and other more complex shapes. Other settingssuch as the population size and the inclusion of crossover operations in the evolutionary algorithms could also be investigated for more diverse shape generations.

ACKNOWLEDGMENT

REFERENCES

[1] F. McGuire, "The origins of sculpture: Evolutionary 3D design". IEEE Computer Graphics Applications 13, 9–11 (1993)
[2] H. Watabe, and N. Okino, "A study on genetic shape design". In: Proceedings of the 5th International Conference on Genetic Algorithms. pp. 445–451. ICGA '93, Morgan Kaufmann Publishers Inc. (1993)
[3] K. Sims, "Evolving 3D morphology and behavior by competition. Artificial Life" 1, 353–372 (1994)
[4] C.J. Jacob, and G. Hushlak "Evolutionary and swarm design in science, art, and music". In: The Art of Artificial Evolution: A Handbook on Evolutionary Art and Music, pp. 145–166. Springer (2007)

[5]   P. Bentley, "Generic Evolutionary Design of Solid Objects using a Genetic Algorithm". Ph.D. thesis, University of Huddersfield (1996)

[6]   A.H. Barr, "Superquadrics and angle preserving transformations". IEEE Computer graphics applications 1: 11-23, (1981).

[7]   A.H. Barr, "Global and local deformations of solid primitives". Computer Graphics, 18(3): 21-30, (1984).

[8]   A. Jaklic, and F. Solina, "Superellipsoids gaining momentum". In: Proceedings of 7th Computer Vision Winter Workshop CVWW'02,, Bad Aussee (2002)

[9]   J. Gielis, B. Beirinckx, and E. Bastiaens, " Superquadrics with rational and irrational symmetry". In: Proceedings of the eighth ACM symposium on Solid modeling and applications. pp. 262–265. SM '03, ACM (2003)

[10] R.J. Preen, L. Bull, "Evolution of Supershapes for the Generation of Three-Dimensional Designs". In Evolutionary Computing 20 Symposium: Proceedings of the 50th Anniversary Convention of the AISB 2014, Goldsmiths, University of London, pages 15-22.The Society for the Study of Artificial Intelligence and Simulation of Behaviour (2012).

[11] R.J. Preen, and L. Bull "Towards the evolution of vertical-axis wind turbines using supershapes", Proc. 50th Anniv. Conv. AISB Evol.Comput. 20 Symp., pp.15 -22 (2014)

[12] B. Barry, "3-D printing: The new industrial revolution". In: Business Horizons 55, 155—162(2012)

[13] J. Gielis, "A generic geometric transformation that unifies a wide range of natural and abstract shapes". American Journal of Botany 90, 333–338 (2003)

[14] A.E.Eiben, and J.E.Smith.Introduction to Evolutionary Computing. (2003).

[15] D.B. Fogel, and L.J. Fogel "An introduction to evolutionary programming". Artif.Evol., 1063: 21-33 (1996)