공학석사 학위논문

Imagination Model: Creating Images via Divergent Search of Compositional Pattern Producing Network

상상 모델: 구성 패턴 생성 네트워크의 다양성 탐색을 통한 이미지 제작

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Abstract

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Divergent Search methods are devised to resolve the problem falling into a trap of local optima, an arch-enemy of stochastic optimization algorithms. Novelty Search and Surprise Search, inter alia, use the concept of *behavior* and explore behavioral space defined by it, maintaining evolutionary divergence and they have shown great performance in this respect. Moreover, coupling novelty and surprise concept was designed based on ideas that those two algorithms search behavioral space in a different way. The combination of two algorithms can be viewed as multiobjective optimization algorithm, and this approach enhanced the performance than using one divergent search method only. Since several divergent search methods have outperformed existing stochastic optimization algorithms in recent studies of robotics, it has been applied to many other domains, such as robot morphology, artificial life and generating images. Particularly, the Innovation Engines applied Novelty Search to image generating method so as to create novel and interesting images. In this paper, we propose Imagination Model that adopts Novelty-Surprise Search which is the combination of Novelty and Surprise Search instead of pure Novelty Search, as an extension of Innovation Engine. Evolutionary algorithms using Novelty Search, Surprise Search, Novelty-Surprise Search are compared via well-trained deep neural networks defining the behaviors of individuals in terms of creating interesting images. Results of experiments indicate that Novelty-Surprise Search outperforms Novelty Search and Surprise Search even in image domain; it searches and explores vast behavioral space more extensively than each search algorithm on its own.

Keywords: Evolutionary computation, Divergent search, Neuro-evolution, Computational creativity

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Chapter 1

Introduction

Imagination is the main driving force for human creativity and ingenuity. Although imagination and creativity are much more sophisticated and complex than their simulation by computers, there still exists the field of research inspired by human mind and trying to abstract them. Art created by computers, computational creativity, has been considered to be an interesting subject and studied by numerous computer scientists as an application of artificial intelligence. Particularly, with the rapid progress of artificial intelligence in recent years, research about generating creative works by artificial intelligence agent not intervened by a human being has been accelerated. Typical example of steep growth in this area is generating images. Computer vision is the area that has seen remarkable growth, following the trend of deep learning. Since image generation is closely related to computer vision, images have become a subject of special interest than writings and music in research community, among the branch of computational creativity.

As in the machine learning community, various methods have been published at the field of evolutionary computation. Compositional Pattern Producing Network[1] is one of the most classic examples in this area. Compositional Pattern Producing Networks are the n-dimensional function that encodes abstracted patterns and regularities. The potential of CPPNs is enough to draw both complex and recognizable image. Explicit fitness measure of Compositional Pattern Producing Networks, however, was indefinite in image domains, interactive evolutionary computation scheme was adopted to evaluate[2, 3] during evolution. That is, results of evolution, images of each individual, are displayed to users in website through GUI interface and they pick a couple of images. Then, algorithm resumes the evolution with individuals picked by users and this process is repeated until users satisfied with output images of evolution.

Over the past few years, the field of machine learning has achieved striking advance with a technology called *deep learning*[4, 5] as mentioned. The Innovation Engine inspired by innovative process of a human being is developed, taking advantage of the circumstance[6]. Deep neural networks can extract the feature from images created during evolution easily and effectively. In other words, deep neural networks permit images produced during evolution process to be evaluated. Although Innovation Engines utilize this scheme, it does not optimize ordinary objective function. Instead of searching directly towards the objective, Innovation Engine exploits divergent search called *Novelty Search*[7]. Novelty Search explores behavioral space, finding solutions that show novel behaviors so as to maintain evolutionary divergence of population. Innovation Engines applied to image domain defines behaviors as outputs of images from deep neural networks. Fusion of CPPNs and novelty search to create endless stream of creating new things is the main gist of the Innovation Engines.

People think that something undiscovered or things deviated from expected ones are imaginative. That's how people imagine. In this paper, Imagination Model inspired by concept of imagination process is proposed. To realize the idea, measurements for undiscoveredness and unexpectedness must be incorporated into the Imagination Model. Novelty metric of Novelty Search can be taken into consideration as metric for what is undiscovered, while the proposed model still requires new method to explain what is unexpected. Another divergent search, the Surprise Search[8, 9] can handle the problem estimating the degree of unexpectedness. Therefore, Imagination Model uses combination of Novelty Search and Surprise Search, *Novelty-Surprise Search* which is even more powerful divergent search than Novelty Search or Surprise Search alone[10, 11]. In this fashion, the Imagination Model can be viewed as an extension of Innovation Engine..

Chapter 2

Background

This chapter surveys divergent search, neuro-evolution method and automated image generation.

2.1 CPPN-NEAT

NeuroEvolution of Augmenting Topologies[12], NEAT is the neuro-evolution method that evolves artificial neural networks, beginning evolution with small and simple architecture which contains only input and output nodes with fully connected connections, no hidden nodes. Each individual network in the population is complexified by adding neurons and connections during evolution process, networks become larger and more complicated over generations. NEAT exploits genotypic structure and historical marking of nodes and connections added during evolution to speciate. The speciation technique permits population to maintain the genotypical divergence and protect innovation, dividing the population into several species that share a common structure. If structural innovation appears in a network during evolution process, the individual network will be assigned to new species and compete within its niche through techniques like fitness sharing. Hence, the appearance of innovative structure is protected by speciation.

Compositional Pattern Producing Network[1] is a function of n-dimension, produces abstracted pattern of n-dimensional space. For instance, Compositional Pattern Producing Networks with two inputs generates two-dimensional images. Compositional Pattern Producing Networks(CPPNs) are represented as a connected graph, i.e. networks of activation functions. While every neuron in classic artificial neural networks shares only one type of activation function, generally sigmoid function or occasionally Gaussian function, CPPNs can use different activation functions for each neuron it has. CPPNs can be evolved by NEAT, for the reason that it is a different type of artificial neural networks. The only difference between NEAT and CPPN-NEAT which evolves CPPNs is that CPPN-NEAT chooses the activation function of newly added node to CPPNs during evolution from a canonical set of activation functions. Original intention of developing the CPPNs is to encode and exploit the geometric regularity of nature, recent studies prove that CPPNs can produce interesting and complex images in whether greyscale or RGB. Further, due to potentiality of CPPNs of encoding the pattern and regularity, CPPNs are used to represent the genome of large-scale neural network in neuro-evolution method with high-dimensional pattern of parameters(hypercube or hyperspace)[13, 14]. Finally, one of the strongest points of CPPNs is that it can express images in infinite resolution because the size of its output image is determined by the input that fed into the CPPNs.

2.2 Novelty Search

Novelty Search is extended version of NEAT. Novelty Search introduces the concept of novelty in behavioral space instead of directly rewarding through objective-based fitness function. In the case of Novelty Search, therefore, novelty must be clarified. Novelty is defined by novel behavior in search space; individuals that are most deviated from the solutions found so far have higher novelty. Thus Novelty Search finds solutions that show novel behaviors with respect to current population and past generation. To achieve that, Novelty Search reserves most novel behaviors found in each generation, by keeping a novelty archive. Based on a certain distance metric, Novelty Search can be formulated generally as follows:

$$n(i) = \frac{1}{n} \sum_{j=0}^{n} dist_n(i, j) \tag{2.1}$$

where j is the j-th nearest neighbor in terms of novelty distance function and $n(i)$ is the novelty score of individual i in current population. Neighbors of the novelty metric are chosen from the current population plus novelty archive.

Distance function of novelty metric and novelty metric itself can be user-defined or customized with consideration for the domain to search.

2.3 Surprise Search

Surprise Search is designed on the paradigm of evolutionary divergence[8, 9] like other divergent search methods, but different from Novelty Search. While Novelty Search rewards unseen behavior in behavioral space, Surprise Search rewards unexpected behavior. First, a prediction model is required so as to evaluate *unexpectedness* of an individual. Accordingly, Surprise Search employs a model that predicts behaviors of current population before the evaluation step of evolution is taken, based on the history of behaviors in past generations. Surprise Search finds unexpected solutions deviated from the expected predictions. Unlike Novelty Search, Surprise Search explores the prediction space instead of searching behavioral space directly. Prediction space is different from behavioral space; prediction space can exceed the scope of behavioral space.

Surprise Search is composed of two phase; prediction phase and deviation phase. In prediction phase, the algorithm or model predicts the behaviors of current population, which is future behaviors on the basis of behaviors in past evolution. The number of past behaviors involved in prediction and the locality of behavioral information are determined and expressed by parameter h and k respectively, and they are formulated via model m:

$$\boldsymbol{p} = m(h, k) \tag{2.2}$$

After the prediction phase, similar to Novelty Search, the deviation phase rewards each individual of current generation based on domain-specific distance metric of n-nearest predicted behaviors of the current population:

$$s(i) = \frac{1}{n} \sum_{j=0}^{n} dist_s(i, p_{i,j}) \tag{2.3}$$

where $s(i)$ is the degree or score of surprise of individual i and $p_(i,j)$ is n closest predictions of i.

2.4 Combining Novelty and Surprise Score

A novel solution found during evolution can be expected from the past generations and vice versa. That is, a solution can be unexpected but concurrently might not be novel. Hence, these two concepts are orthogonal. Gravina *et al.* has revealed that coupling novelty and surprise is great method to explore search space with a fashion of divergent search[10]. In the paper, the authors suggested linear combination of novelty and surprise score, the simplest multi-objective optimization technique:

$$ns(i) = \lambda \cdot n(i) + (1 - \lambda) \cdot s(i) \tag{2.4}$$

Evolution and search towards the unseen behaviors and unexpected behaviors simultaneously are accomplished via the model combines novelty and surprise metric.

2.5 Innovation Engines

In previous works, generating creative images through CPPNs has adopted an interactive evolutionary computation scheme. Images chosen by people survive and continue to be evolved. These frameworks are usually provided through web service[2, 3]. When people select plausible images from a set of images generated by an initial population of CPPNs by clicking it in web browser, evolutionary framework evolves CPPNs that produce selected images. Nguyen *et al*. proposed a model that can automatically generate interesting and novel images endlessly, the Innovation Engines, inspired by mechanism of curiosity and how humans create ideas. In the paper, authors use two methods to evolve CPPNs, MAP-Elites[15] and Novelty Search. MAP-Elites keeps an archive of image classes which users want to generate, and at every iteration one of the members of the archive is chosen and evolved. But primarily, evolving CPPNs through Novelty Search is the main contribution of the paper. Behaviors of CPPNs are defined by output vectors of deep neural networks called *deep distance function*. The deep distnace function is a well-trained convolutional neural network on large dataset such as ImageNet[16].

Chapter 3

Methods

3.1 Image Generator

The proposed model uses Compositional Pattern Producing Networks to generate images. CPPNs are evolved by neuro-evolution method, CPPN-NEAT, which requires domain-specific fitness function. But instead, novelty metric and surprise metric are adopted to increase behavioral divergence, novelty and surprise score substitute for fitness of the population. Other methods to draw pictures from numerical information like vectors, such as deconvolution method used in Deep Convolution Generative Adversarial Networks[17] must determine the size of output images before the architecture of the network is defined. Hence, CPPNs that can produce an image in any resolution, almost infinite, is adopted.

3.2 Behavioral Space

Novelty Search is originally devised to solve problems in robotics. Maze navigation is the representative problem in that domain. This specific kind of problem domain can easily evaluate behavior, defined by ending position and its coordinate in a maze, of the navigating agent. Understandably, maze itself is considered as behavioral space. Behavioral space in the domain of generating images and classifying them, however, is not simply established. If behaviors of CPPNs are defined by images generated from them, behavioral space is too vast to explore, almost infinite and intractable. Even images contained in MNIST, one of the simplest image dataset, are matrices of 28x28, 784-dimensional vector, which is too large. In this paper, images of 256x256 are mainly treated, therefore a method to reduce the dimensionality is required. In addition, in previous research, novelty metric naively defined by l1 distance of each pixel in two images is examined[6]. The test result in that paper indicates that kind of metric is not a good choice.

Thus extracting a feature from the image through deep neural networks can be highly promising option in this situation. Because deep neural networks have shown that huge success in the field of computer vision, such as image classification, it outperforms even humans under certain circumstances. Deep neural networks especially convolutional neural networks, therefore, are used to express behavior from generated images; it is a function that maps an image generated by CPPN into its behavior, namely, *deep distance function*[6]. An output of deep distance function is an n-dimensional vector, this feature is used to determine novelty of CPPN by calculating the Euclidean distance to other features in archive, current population or a set of predictions.

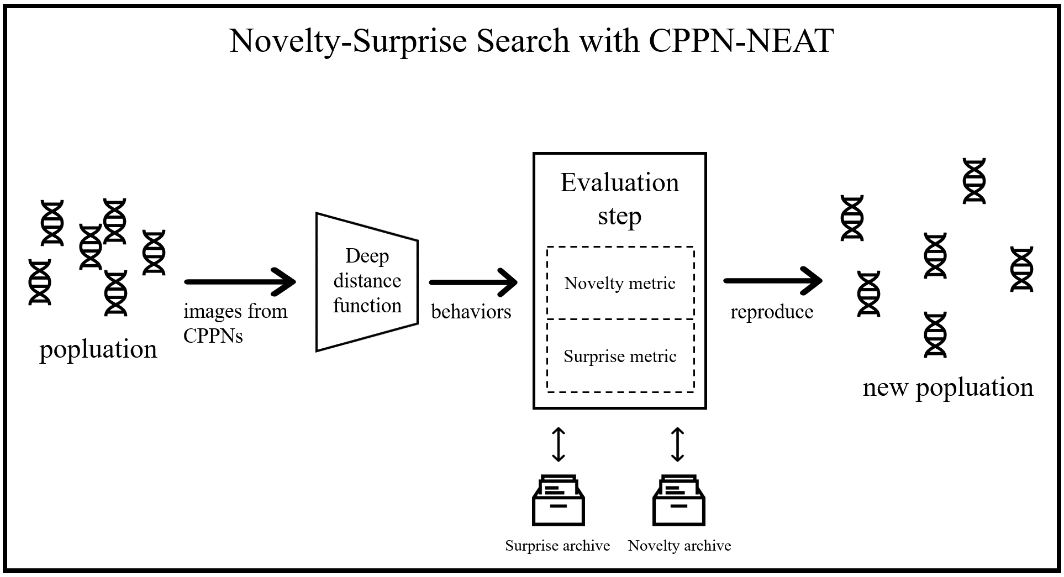


Figure 3.1 Abstracted overview of the Imagination Model

3.3 Imagination Model

The Imagination Model proposed in the paper combines three different methods; CPPN-NEAT, fusion of two divergent search methods and deep neural networks. Figure 3.1 depicts the high-level overview of the Imagination Model. From genotypes of the current population, phenotypes i.e. CPPNs are interpreted then they produce images. Those images are fed into deep distance function, which is deep neural network well-trained on large dataset, being transformed into vectors called behaviors. Then, novelty score and surprise score are calculated according to novelty and surprise archive. After that, overall fitness of an individual is computed by means of a linear combination of its novelty score and surprise score. Finally, based on the fitness of each individual, reproduction and speciation step are taken to create a new population. This illustration describes only one aspect of domains that Imagination Model can apply, image generation. Different domains or fields such as natural language generation, level-design of games also can be incorporated by Imagination Models using different structures, models, methods, and algorithms.

Chapter 4

Experiments

The experiment domain for the paper is generating novel, complex and creative images or abstracted patterns. The performance of Novelty Search, Surprise Search and Novelty-Surprise Search is measured by exploration and exploitation in both behavioral space and search space. Furthermore, another point to determine which method performs well is how interesting images that they create are.

4.1 Fitness Measure

Fitness measure experiment is carried out to compare three divergent search algorithms. Surprise Search and Novelty-Surprise Search are tested primarily, while Novelty Search is included as baseline algorithm, due to the Innovation Engines. All methods utilize CPPN-NEAT with the same hyperparameters, to evolve CPPNs and generate complicated images. AlexNet[18] is employed as a baseline deep distance function to obtain behaviors by extracting a feature from images generated by CPPNs. Each evolution is carried on a population of size 200, for a maximum of 2000 generations. The minimum number of generation is 1000.

This experiment also treats λ, investigating the difference of the performance by changing the value of λ. The baseline value of λ is 0.6 in accordance with previous researches that introduce coupling novelty and surprise[11]. But even then, we test with a different λ from 0.1 to 0.9 in increments of 0.1. Other hyperparameters are chosen empirically; the number of clusters in prediction phase of Surprise Search is 15, the number of neighbors in novelty and surprise is 15 and 8 respectively. Novelty threshold and surprise threshold are updated during evolution in an adaptive manner.

4.2 Deep Neural Networks and Dataset

In order to test the effect of deep distance function, ImageNet[16] is used. ImageNet is a large computer vision database, which contains over 14 millions of images including fish, bird, vehicle, person, etc. During the experiment, several well-known and published convolutional neural network architectures are examined for evaluation step. VGG[19], DenseNet[20] and Xception[21] is selected from a number of candidates, including AlexNet as a baseline network. According to the benchmark of CNNs, VGG and DenseNet are in the middle ranks and Xception displays great performance to challenge top-level whereas AlexNet places the lowest position. Besides them, there are numbers of well-known convolutional neural network architectures, most of them, especially with a great number of parameters, are excluded because their computational cost to evaluate is too high.

All of the networks require preprocessing step of input data. Basically, VGG, AlexNet, and DenseNet need 10 modified 3x224x244 images from an original 3x256x256 RGB image. The original image is resized into 224x224 image, cropped from left, right, up, down and center. And their horizontal reflections are included, then the total 10 instances are produced from the original image. The mean of the output vectors of 10 instances, printed out from CNNs is assigned to the original image as an actual feature of it. In the case of Xception, input images must be preprocessed same as the cases of VGG, DenseNet and AlexNet, but an original 3x384x384 image is transformed into 10 instances of size 3x299x299.

All the experiments are conducted on a machine with Intel i7-6850k CPU @ 3.6GHz and four GeForce GTX 1080Ti GPU cards. Python, PyTorch[22] and scikit-learn[23] are used for implementation.

Chapter 5

Results

Table 5.1 describes the influence of parameter λ in Novelty-Surprise Search, showing mean and standard deviation of distances from the centroid of novelty and surprise archive to all other points. The result which is maximum among 15 trials is presented. λ value that puts way more weight on one metric than the other shows poor performance noticeably. The values ranging from 0.3 to 0.7 are good choice for Novelty-Surprise Search, particularly 0.6 can be the best option. Another interesting point is that balanced λ values i.e. from 0.3 to 0.7 keep higher novelty score than higher λ values and higher surprise score than lower λ values. It is a one piece of evidence that supports the idea that the combination of novelty and surprise searches larger space than the method that uses only novelty or surprise. The selected λ value is 0.6 for the rest of the experiments.

Results on ImageNet to compare divergent search algorithms are indicated in Figure 5.1 and Figure 5.2. It shows mean and standard deviation of distances from a centroid to all points in the archives. Previous paper about coupling novelty and surprise[10] revealed

Table 5.1 Result of selecting λ for Novelty-Surprise Search

	Novelty archive		**Surprise archive**		**Total**	
λ	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
0.1	55.4	10.6	70.2	13.5	64.3	13.4
0.2	59.9	11.9	68.8	19.6	65.2	15.8
0.3	61.2	11.7	71.3	11.4	66.8	12.4
0.4	60.4	11.1	71.4	15.8	66.7	14.5
0.5	60.1	11.3	72.8	13.2	66.9	13.9
0.6	62.9	11.7	72.3	14.2	67.8	13.8
0.7	61.7	12	71.6	13.1	66.9	13.6
0.8	59.2	11.2	68.2	12.1	63.9	12.5
0.9	58.6	10.7	69.1	11.7	64.4	12.5

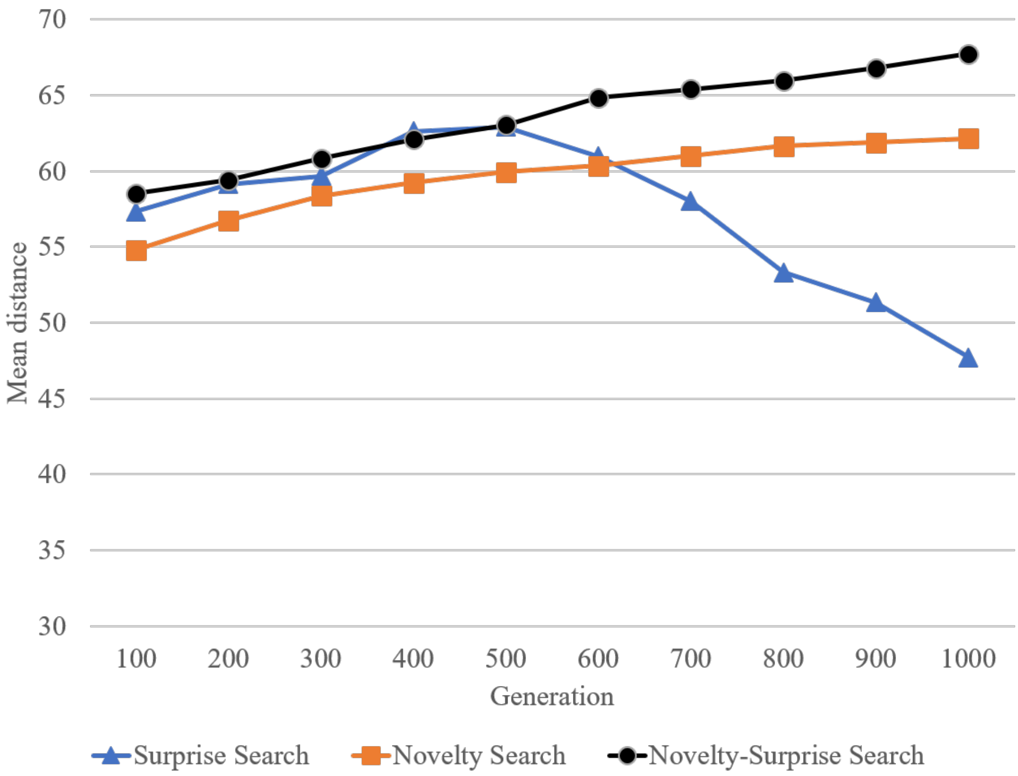


Figure 5.1 Mean distances from centroid over generations

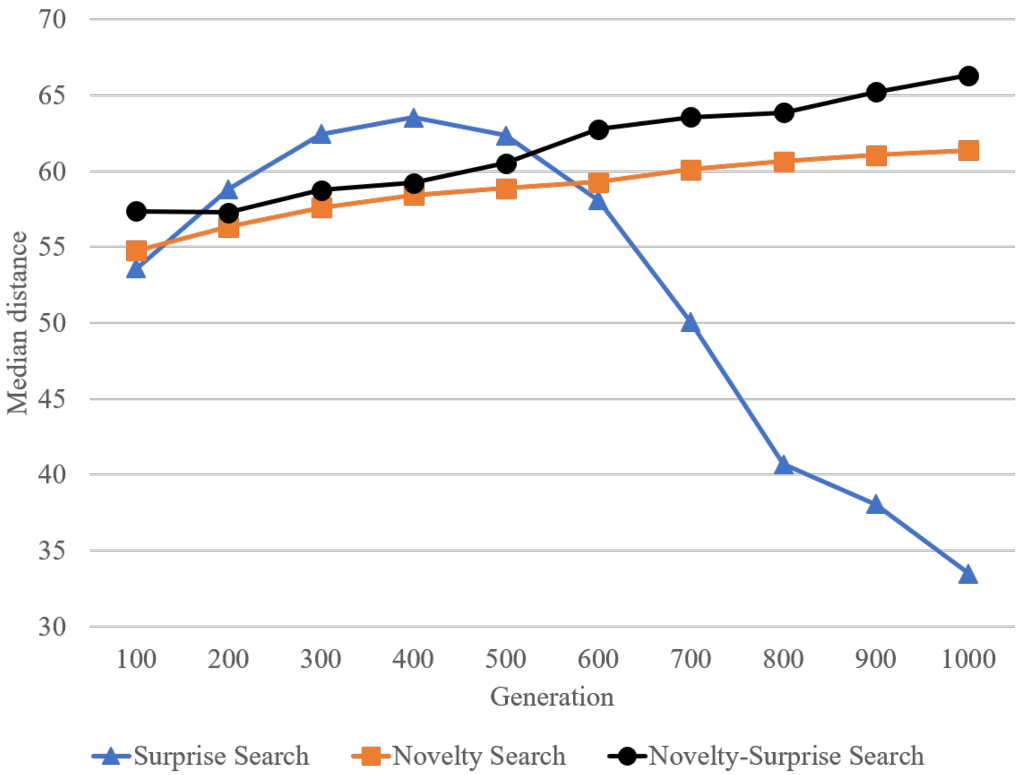
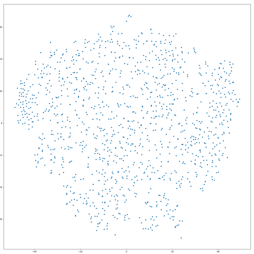


Figure 5.2 Median distances from centroid over generations

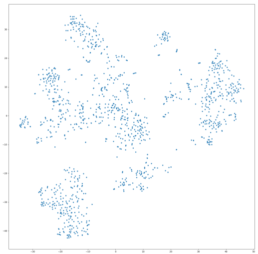
that Surprise Search shows poor performance in some case, called *circular behavior*. As other methods, mean distance of surprise archive in Surprise Search increases for a couple hundred generation. After few hundreds of generations, it starts to decrease and continues to reduce until evolution process ends. For Surprise Search only, this is a critical problem. On the other hand, behaviors in surprise archive of Novelty-Surprise Search keeps spreading out, showing their mean distance from centroid increases constantly. Total behaviors of Novelty-Surprise Search, also, are more scattered than behaviors stored in the archive of Novelty Search.

Mean and median of distances from centroid of the archive to all points in the archive of Novelty Search and Novelty-Surprise Search are compared via nonparametric test. Comparing both representative values of 10 runs is indicative that Novelty-Surprise Search outperforms Novelty Search in the manner of evolutionary divergence($p < 0.05$ via Mann-Whitney U Test, also known as Wilcoxon rank-sum test).

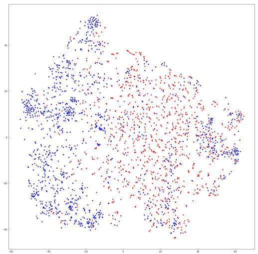
In order to visualize behaviors in an archive, which is a set of the best individuals in each generation, we should reduce the dimensionality of behavior vectors. Principle Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE) are employed to achieve it. Results are illustrated in Figure 5.3. Behaviors in novelty archive, regardless of Novelty Search or Novelty-Surprise Search, are widely diffused, whereas ones in surprise archive form several clusters deployed distantly in behavioral space. Particularly, it seems that surprise archive of Surprise Search is more clustered than Novelty-Surprise Search. But total behaviors in novelty archive plus surprise archive in Novelty-Surprise Search show comprehensive aspect of Novelty-Surprise Search, as illustrated in the picture (c) of Figure 5.1. Red points and blue points represent behaviors from novelty archive and surprise archive respectively. Surprise behaviors cover the undiscovered region by novelty archive



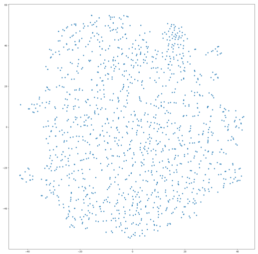
(a) Novelty archive



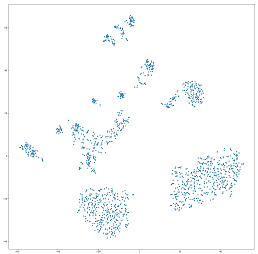
(b) Surprise archive



(c) Total



(d) Novelty archive only



(e) Surprise archive only

Figure 5.3 PCA and t-SNE results on novelty and surprise archive after 1000 generations

Table 5.2 Result of experiments about deep distance function

Architecture	Image size	Crop	Mean distance	
			At 100 generation	At 1000 generation
AlexNet	3x256x256	10 crop, 3x224x224	50.4	66.4
VGG	3x256x256	10 crop, 3x224x224	42.6	57.1
DenseNet121	3x256x256	10 crop, 3x224x224	4.64	5.46
Xception	3x384x384	10 crop, 3x331x331	6.41	7.11

and vice versa. This observation denotes that both novelty and surprise complement each other.

The experiment results about deep distance function are listed in Table 5.2. All Novelty-Surprise Search algorithms explore behavioral space more extensively over generations no matter which deep distance function is used. However, a direct comparison for investigating how deep distance function affects to NSS cannot be carried out, since those deep neural networks have different hyperparameters, architecture and parameters. As indicated in Table 5.2, the range of behaviors i.e. the range of output vector extracted from each deep distance function is different from each other. Eight runs for each deep distance function are conducted.

Pictures in figure 5.4 and 5.5 are images that are generated from Novelty Search and Novelty-Surprise Search. Figure 5.4 are images that are recognizable by human and simple, while images of figure 5.5 are complex and even more irregular.

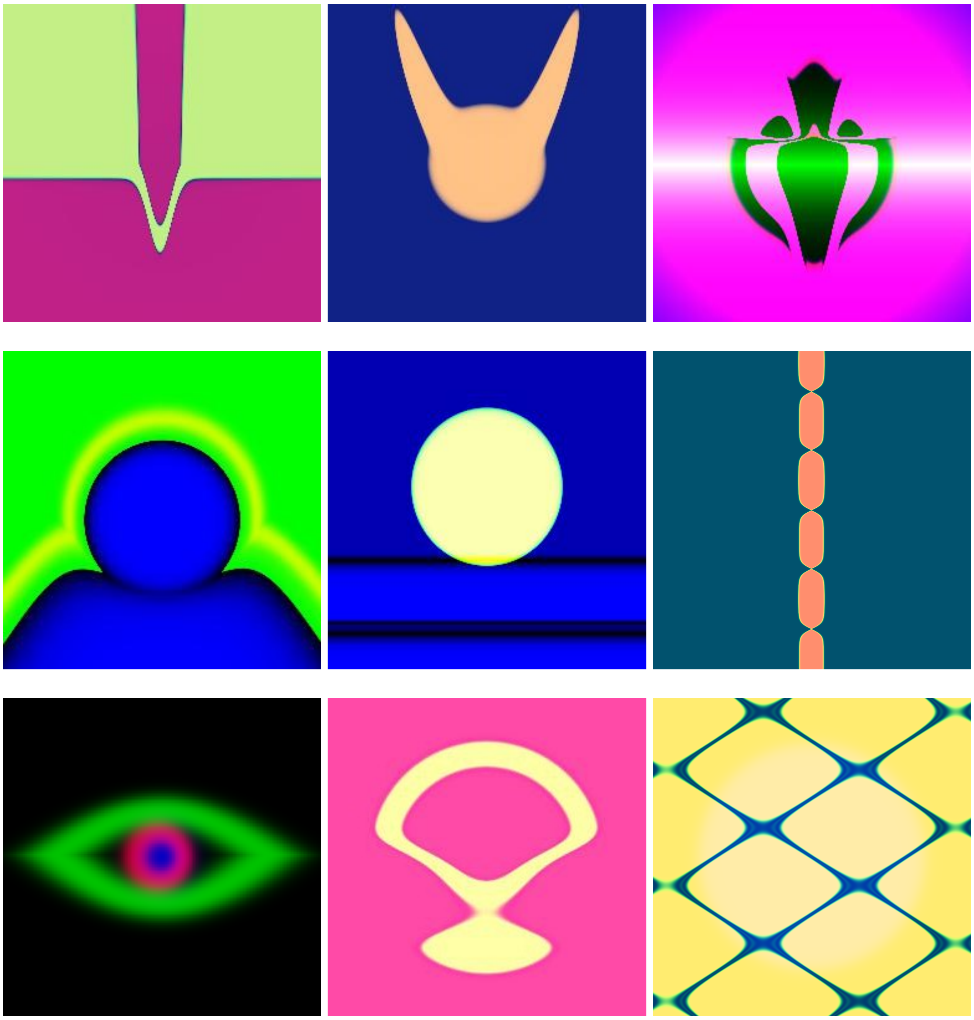


Figure 5.4 Simple and recognizable images generated by Novelty-Surprise Search

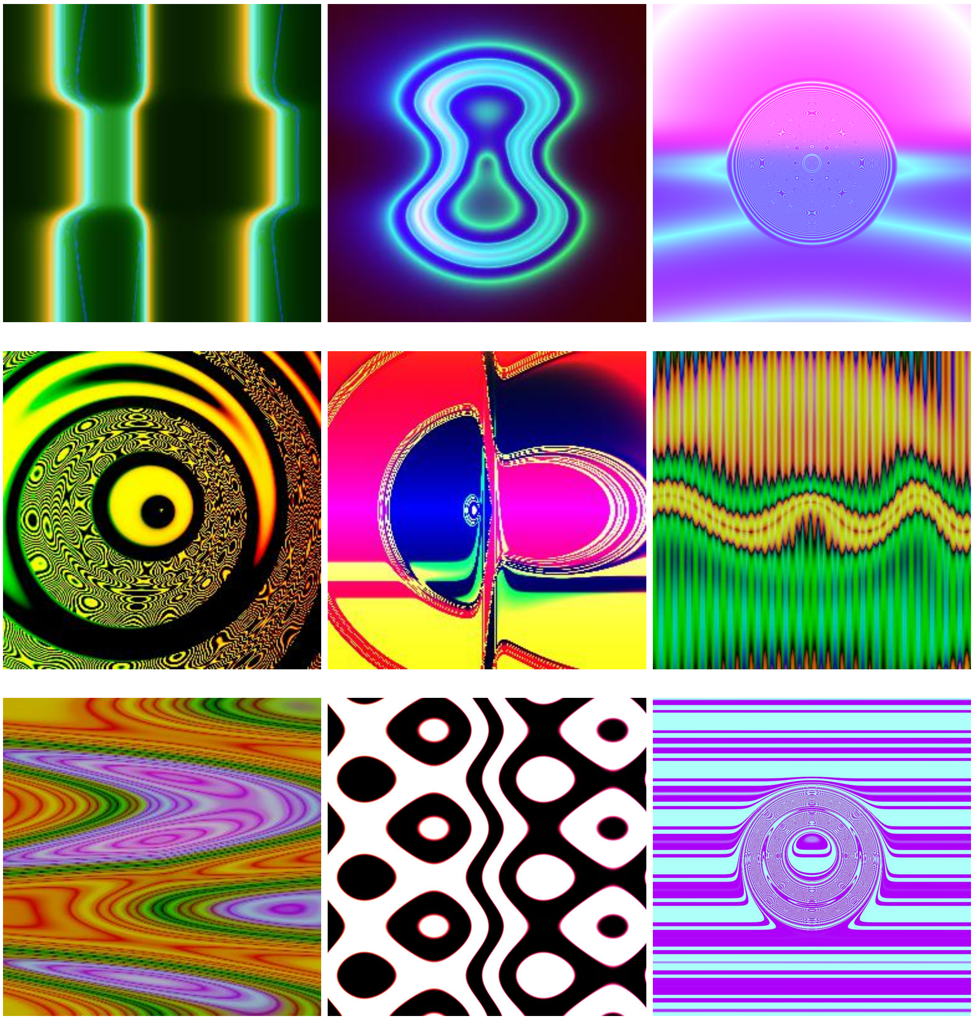


Figure 5.5 Complex images generated by Novelty-Surprise Search

Chapter 6

Discussion

Imagination Model that utilizes fusion of surprise search and novelty search in the domain of generating creative images is introduced in this paper; it can be considered as a modified version of the Innovation Engine. As seen in the results, behaviors of CPPNs evolved by Novelty-Surprise Search are more diffused in behavioral space than those found by Novelty Search alone. In other words, Novelty-Surprise Search searches behavioral space more exploratively than Novelty Search in the same amount of generation. Moreover, Surprise Search suffers from the circular behavior problem which is to keep searching for behaviors found before already, but Surprise Search in Novelty-Surprise Search can handle that problem, fueled by Novelty Search. Likewise, Some regions of behavioral space that Novelty Search cannot search can be explored by Surprise Search in Novelty-Surprise Search. Thus, according to observation of experiments, Novelty Search and Surprise Search in Novelty-Surprise Search turns out that they are complementary to each other, showing some sort of cooperative co-evolution. From the perspective of memory usage, Novelty-Surprise Search

occupies memory space only twice as much as Novelty or Surprise Search, due to maintaining two archives of novelty and surprise. Thus there is no severe flaw in memory use.
There are several ideas that can be investigated in future works:

Even though CPPNs are much lighter than typical feedforward neural networks like convolutional neural networks, only one image can be generated from each CPPN, but with various resolutions. This is one of the main drawbacks of CPPNs. This problem can be resolved by extending the structure of CPPNs. Additional inputs of latent variable are fed into CPPNs with coordinates information. By controlling them, a CPPN can produce different images without further evolution.

A new method of prediction phase in Surprise Search can be proposed. But the method must be compact because computation cost is a critical problem. For example, an artificial neural network that receives behaviors of past generations as an input and yields predictions as an output could be adopted instead of k-means clustering and linear regression currently used. The artificial neural network will be trained on the past generations of the current population; if data is accumulated over generations, the prediction model can make more and more precise predictions.

Chapter 7

Conclusion

Imagination Model is the system that embodies computational creativity and simulates imagination process of a human by combining two representative Divergent Search methods, i.e. Novelty Search and Surprise Search. Like in the paper of Innovation Engine, this paper introduces a brief sketch of Imagination Model, testing the model in domain of generating creative images. Since deep neural networks can abstract given data and extract features well from them, behavior for divergent metric of images generated by evolution of CPPNs is defined by output features of convolutional deep neural networks trained on large image dataset. The experiments results indicate that Novelty-Surprise Search can be advantageous in terms of evolutionary divergence. Namely, Novelty-Suprise Search can be more explorative in behavioral space than Novelty Search or Surprise Search alone. Exploring a larger behavioral space can be interpreted as that more new individuals can be found within the same time frame with higher probabilities. Eventually, this result can lead to conclusion that Imagination Model can create more diverse images than Innovation Engine. Also, similar to Innovation Engine, Imagination Model can be applied to numerous domains. Computational creativity through Imagination Model could ultimately provide endless inspiration like literature and art of humankind.

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요약

다양성 검색 방법은 확률적 최적화 알고리즘의 주적인 지역 최적해의 함정에 빠지는 문제를 해결하기 위해 고안되었다. 그중에서도 참신함 탐색과 놀라움 탐색은 *행동*이라는 개념과 그 개념이 정의하는 행동 공간을 탐색하며 진화적 다양성을 유지했고 이 점에 있어서 훌륭한 성능을 보여주었다. 그뿐만 아니라 두 다양성 탐색이 서로 다른 방식으로 행동 공간을 탐색하는 데에서 착안하여, 참신함과 놀라움을 결합하는 알고리즘이 설계되었다. 두 알고리즘의 조합은 다목적 최적화 알고리즘으로 간주할 수 있는데, 이 접근 방식은 둘 중 하나만의 다양성 탐색 방법을 사용할 때보다 성능이 개선됨을 다양한 연구에서 보여주었다. 이처럼 여러 다양성 탐색이 기존의 확률적 최적화 알고리즘을 뛰어넘는 성능을 보였기 때문에, 로봇 형태학, 인공생명, 이미지 생성처럼 다양한 분야에 응용되어왔다. 특히, 혁신 엔진은 새로우면서도 흥미로운 이미지를 창조하기 위해 이미지 생성 방법에 참신함 탐색을 적용했다. 이에 더해 우리는 이 논문에서 상상 모델을 제안한다. 이 상상 모델은 혁신 엔진의 확장으로서 순수한 참신함 탐색 대신 참신함 탐색과 놀라움 탐색을 결합한 참신함-놀라움 탐색을 도입한다. 참신함 탐색, 놀라움 탐색 그리고 참신함-놀라움 탐색을 사용한 진화 연산을 이미지 생성에 관한 측면에서 비교하는 실험을 진행하며, 이들은 모두 심층 인공신경망을 통해 그들이 사용하는 행동이라는 개념이 정의된다. 실험 결과를 살펴보면, 참신함-놀라움 탐색은 단순히 참신함 탐색이나 놀라움 탐색 각각을 따로따로 사용하는 것보다 더 넓은 행동 공간을 더 광범위하게 탐색하는 모습을 보여주었다. 이로부터, 다른 분야뿐 아니라 이미지 생성 영역에서도 참신함-놀라움 탐색이 참신함 탐색과 놀라움 탐색 각각을 뛰어넘는 성능을 보인다는 것을 확인하였다.

주요어: 진화 연산, 다양성 탐색, 신경망진화, 계산 창의성

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