Artificial Immune System Based Art

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Abstract

Creating visual art using biologically inspired techniques is a new and exciting field. We describe an interactive image generation system based on an Artificial Immune System (AIS). In our system the user guides image evolution by cueing the system about the aesthetic content of selected areas of images in the current population.

Introduction

Even though art is traditionally defined as a typically human occupation, in recent times computers have found their way into the artistic process through what can be called "Artificial Art".

Research on this subject was started simultaneously with the first studies that theorized about the artistic possibilities of an intelligent machine. Turing, for instance, started the design of a basic programme for the creation of poetry (Hodges 2000) and Ada Byron considered the possibility of creating music with computers (Romero 2002).

For some researchers, computer science is a fundamental part of the future of art. Recent works have even focused on the creation of computational artists and critics, which possess their own aesthetics and are therefore independent from the human being (Sims 1991), (Baluja 1994), (Rowbottom 1999), (Manaris 2002), (Machado 2004). However, most of the current artificial art systems are tools that allow human beings to create their own art works.

The type of interaction with the user and the underlying computational techniques are two key aspects in these systems.

There are several types of interaction methods between user and machine, including supplying examples, handling of controls and parameters, evaluating the generated works, etc.

User evaluation of the produced pieces is the most popular approach in Evolutionary Computation systems, giving rise to what is usually called the Interactive Evolutionary Computation (IEC) paradigm. An extensive state of the art of this type of system can be found in (Takagi 2001).

In our approach, the user interacts with the system by selecting areas of the images that are considered interesting, which is, as far as we know, a new approach in the context of IEC.

Several types of Artificial Intelligence techniques have been applied to the development of artificial art systems. In recent years, nature-inspired techniques have been widely used due to their adaptive capacities. For instance, Artificial Neural Networks and various Evolutionary Computation techniques were applied to the creation of visual art and music. In the field of visual art, to which this paper refers, the seminal work of Karl Sims (Sims 1991), resorting to Genetic Programming (GP), is probably the most influential one.

The capacity of Artificial Immune System (AIS) based approaches to learn and discern between the usual and the new make them excellent candidates for these types of tasks. However, the work of (Chao 2003) was the only one found where AIS is used for art-related tasks (Chao 2003).

In said work, the AIS is in charge of discarding those solutions which, in principle, are less similar to the user's aim. It uses for this purpose some distances between the various elements which are based on Minkowski's metrics. In this work, those elements having a greater distance from the subsequent choices made by the user are discarded, thus reducing the search space. Biomorphs are the example used in order to test this algorithm (Dawkins 1986).

We present an interactive art generation system based on AIS which relies on mathematical tree-like expressions to generate visual art according to user preferences.

The following section introduces some key concepts about GP and AIS. We then describe our system specifying: the specific characteristics of the AIS used, the image representation method and the interaction mechanism. We also present a short description of the system behaviour from the point of view of the user, as well as some experimental results. Finally, we draw some conclusions and point out at some future developments of the proposed system.

Fundamentals

In this section we describe some concepts of GP relevant to our system and introduce some basic notions related to AIS.

Genetic Programming

In 1992, John Koza (Koza 1992) established the basis of Genetic Programming, an Evolutionary Computation approach that allows the evolution of computer programmes.

In Koza's proposal the individuals (computer programmes) are codified as expression trees composed by function and terminals.

In our case, a tree represents a mathematical expression by means of the existing relationship between the function and its arguments, the function being the father of the arguments.

There are several types of recombination and mutation operators. We resort to standard genetic operators, namely: swap tree crossover and generate random tree mutation.

The crossover operation yields two new trees by exchanging two random selected subtrees from the parent trees, as shown in figure 1.

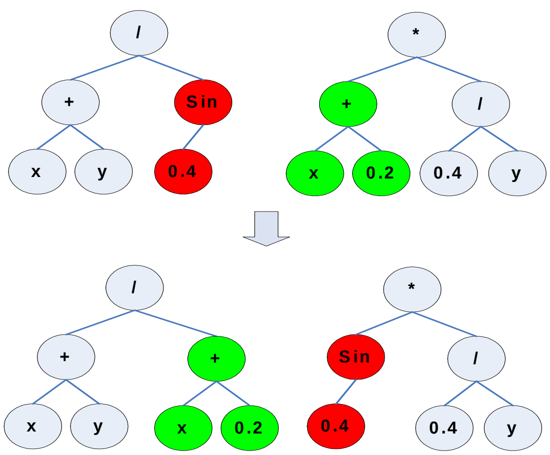

Figure 1. Example of the crossover operation.

The mutation operation generates a new subtree that replaces a randomly selected one from the progenitor (figure 2).

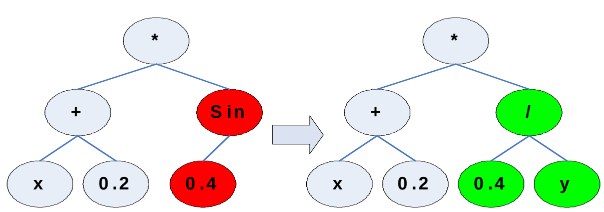

Figure 2. Example of the mutation operation

Artificial Immune System

The Artificial Immune System is a new research area which, based on the available knowledge of the functioning of the immune system, tries to create computational models that emulate, as closely as possible, the global behaviour of the immune system or of some of its processes.

The biological immune system consists of a set of cells, molecules and organs, whose main objective is to maintain the organism in good health by defending it from the attacks of harmful external agents (anomalies) – antigens. The complexity of the immune system is astounding. In fact, it has been compared to the complexity of the human brain (Dasgupta 2001).

Some of the characteristics of the immune system related to the learning process are:

- It recognises elements that belong to the system as opposed to those that are foreign.
- It discriminates between the usual and the new.
- It learns solutions to new problems on the basis of previous experiences.
- It memorises the anomaly and the response to the anomaly.

Some computational models emulate processes or characteristics of the biological immune system considered to be useful. Among the most relevant models are the immune network theory, the negative selection theory and the clonal selection theory.

The clonal selection theory, proposed by Burneo in 1978, explains how the immune system responds to the presence of an antigen through the proliferation of similar lymphocytes.

When an antigen is detected by the system, the lymphocytes which are most similar to it are stimulated and undergo an asexual reproduction process. This process consists of clonation: the creation of a large amount of copies of each parent.

The clones segregate antibodies which are subject to a mutation process in order to reach a specific affinity with the invading antigen. Those clones which turn out to be harmful to the organism, or with poor affinity, are eliminated. The clones with high affinity eliminate the antigens. Once the threat is removed, the system returns to its point of balance by eliminating the surplus of clones (self-regulation).

Artificial Immune-Evolutionary Artist

We start by presenting a global description of the system from the perspective of the user. We then explain the underlying mechanisms, namely: image representation and the AIS employed. Finally, we show the preliminary results obtained by the system.

General Functioning

The purpose of our system is to generate images according to the preferences of the user. In each generation phase, the system presents four images to the user (see figure 3).

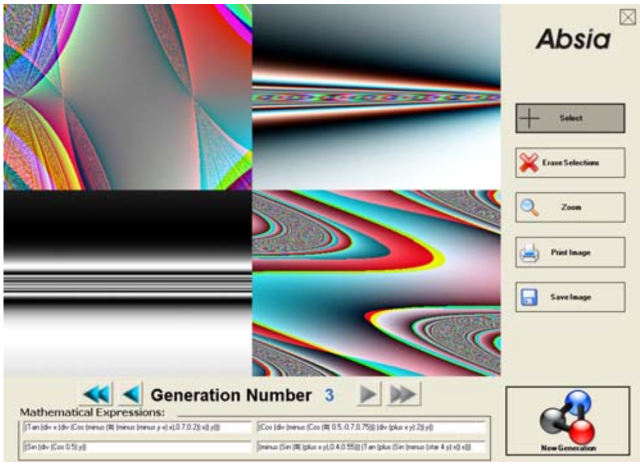

Figure 3. Interface of the system.

Two scenarios may arise: either the user does not like the presented images, in which case none of the areas will be selected, or the user identifies one or various areas as pleasant or interesting.

If the user does not select any area at all, the system creates new images by recombining expressions belonging to the system memory and by randomly generating new images.

When the user selects one or more areas, the system will generate a new population of images with high affinity to the selected areas. This is accomplished by the AIS system that will described in an upcoming section.

Conceptually, the search process consists of two phases:

- The search for interesting images, during which the search space is explored by means of crossover and random generation.
- A refinement phase, which offers variations on a given solution through the search of similar elements by means of the AIS system.

Representation

It is essential that the images can be represented in a format allowing the application of the usual Evolutionary Computation operations. In this case the images are visualisations of mathematical expressions coded in tree format.

The considered mathematical expressions use two variables, x and y, referring to the Cartesian axes. These variables are limited to real values between -1 and 1.

In order to codify the colour information, we use an operator, represented by "#(*r*,*g*,*b*)", which specifies different values for each colour channel. For instance, considering the expression *[(x + y) * #(0.1, 0.2 * x, 0.4)]*, depicted in figure 4, the values of each channel would be calculated as follows:

- Red: (x+y) * 0.1
- Green: (x+y) * 0.2*x
- Blue: (x+y) * 0.4

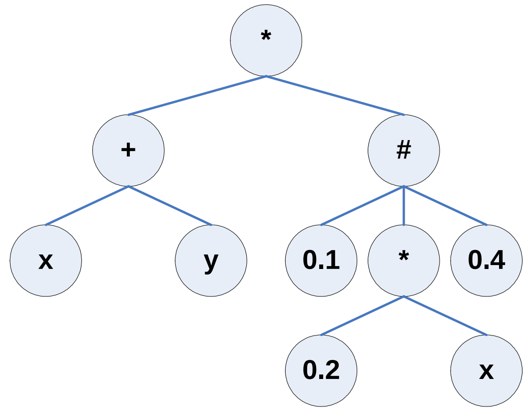

Figure 4. Mathematical expression yielding colour information.

This channel separation concept was taken from NEvAr, a project carried out by Penousal Machado which generates art through evolutionary computation (Machado 2002), which was inspired in Karl Sims' work (Sims 1991). In figure 5 we show a mathematical expression and the corresponding colour image.

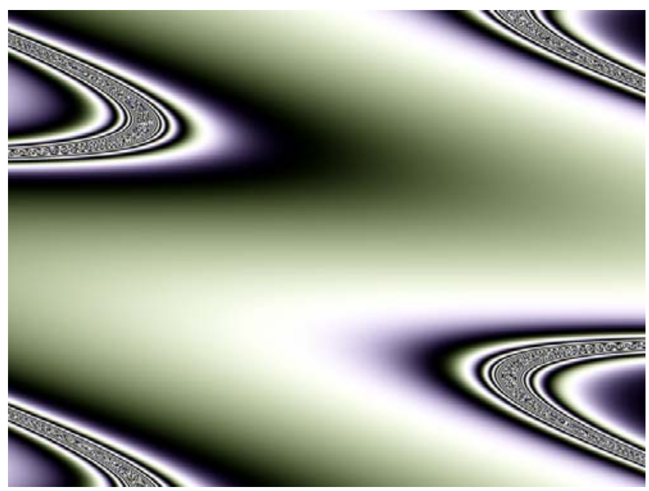

Figure 5. Image resulting from the expression (sin(+(tan(+(sin(-(* 4 y) x)) x)) #(0.4,0.5,0.2))).

The system was designed taking into account its future expansion. It includes a module which manages the evaluation of the expressions. This "Evaluator" starts by converting the tree in three mathematical expressions (one for each colour channel). Then, it dynamically creates a class containing a method to return a matrix with the obtained values after evaluating the expressions for x and y between -1 and 1. Once that class is created, the system compiles it in memory and calls the method to obtain the matrix with the results. The images are then drawn according to this matrix.

The grammar of the mathematical expressions was built with Antlr, a free software developed in Java that is oriented towards the generation of lexicons, syntaxes and grammars (www.antlr.org). We can easily add new elements by calling the Antlr compiler with the new language definition, upon which it generates the classes that are used in the system. Once generated, these classes are compiled as a module and added to the application.

The Artificial Immune System

In this section we analyse the structure of the AIS and describe its functioning.

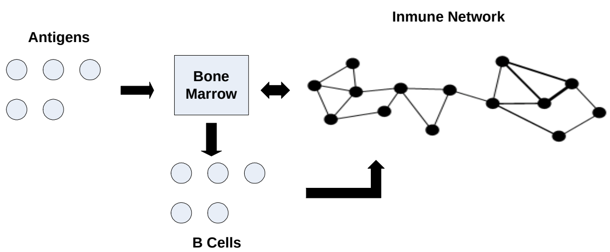

Figure 6. Artificial Immune System design.

Figure 6 shows the design which was used for this system. As usual in computational emulations of biological or natural systems, we had to simplify the system since it is rather complex.

There are four fundamental elements: the antigens, the immune network of antibodies, the B cells and the bone marrow.

- The antigens contain mathematical expressions with high relevance to areas selected by the user.
- Each antibody is a mathematical expression coding an image previously generated by the system. As a whole, the antibody network can be seen as an image repository.
- The B-cells store the antigen—antibody pair and its affinity level.
- The bone marrow is in charge of coordinating the process.

When the user selects image areas, the system determines which subtrees have a larger contribution to the visual aspect of the selected area.

This is accomplished by in the following way:

- We begin by considering all subtrees of the original expression with a root node between n and m, where n and m are empirically defined constants.
- For each pixel of the selected zone we compare the distance between the original image and the one resulting from each subtree.

The relevance of the subexpressions to the selected zones is determined according to the similarity among the pixels. The most relevant expressions will be the antigens of the system.

The antibody network is composed by a set of antibodies (mathematical expressions) linked by affinity relations. The affinity between mathematical expressions is determined by performing a top-down structural comparison of the trees, which means that two trees with different root nodes will have a zero affinity.

The antibody network behaves as an associative memory: depending on its content, each antibody is located in a specific area and has relation with closely linked ones.

The design and the AIS principles are based on a previous work by J. Hunt et al., named Jisys (Dasgupta 1998), financed by the UK government and aimed at detecting mortgage frauds. The information stored in the AIS memory and the Jisys operators were however specific for the fraud detection task, which is why the present system uses a different structure and different operations. As is the case with Jisys, each antibody has at most four links with the other antibodies. This characteristic determines the number of iterations necessary to transverse the network.

The bone marrow generates a set of B-cells. Each B-cell contains an antigen. These B-cells are presented to the antibody network. The antibodies with higher affinity relations with each B-Cell are determined by using the structure of the network

The trees of the selected antibodies are cloned and mutated according to the theory of clonal selection, which generates a large amount of related expressions.

From these expressions the B-cells select the ones which have higher affinity with the antigen of the B-Cell, storing the antigen, antibodies and antigen-antibody affinities.

The bone marrow determines which antibodies will be used in the next generation. This is accomplished by considering the affinity between antibody and antigen, and the area of the zone associated with each antigen. Trees that respond with a greater affinity to larger selection are preferred.

In summary, the AIS process consists of the following steps:

1. The user selects the areas which are the most appealing.
2. The system generates antigens (subtrees) which are relevant to the selections of the user.
3. The bone marrow generates B-cells containing the antigens.
4. The B-cells enter the antibody network causing the mutation of those antibodies which are the most similar to the antigens, storing the most similar antibodies and the affinity relations.
5. The bone marrow selects four antibodies which are representative of the selected zones among the most similar antibodies provided by the B-cells.
6. These antibodies will constitute the next population.

When the user does not select any areas, the images belonging to the population are discarded. The new generation is created by performing the crossover of the present trees in the antibody network. Each of these new trees is used in order to restructure the elements of the immune network and to readjust the weights among them.

Experimental Results

As is typically the case in art generation systems, it is difficult to make an objective assessment of the results. At this point we are primarily interested in assessing the virtues and shortcomings of the system as a tool. In particular we want to assess the user satisfaction at different stages of the evolutionary process: exploration and refinement.

We have carried out some preliminary experiments with fifteen university students having limited art knowledge. We gave them a brief explanation of the tool, and the instruction to conclude the experiments when they found the produced images to be satisfactory according to their own preferences. The tests were performed sequentially, using the same installation of the tool.

On average, the sessions had a duration of approximately 30 minutes. In all cases the users expressed their approval of the final results and their satisfaction with the interactive experience. These limited tests indicate that the system is able to generate images matching the aesthetic preferences of the users.

It is interesting to note that the average time needed to create satisfying images decreased as the number of experiments increased. A possible explanation for this occurrence lies in the behaviour of the AIS.

The experiments were conducted in succession. Thus there was an adaptation of the Artificial Immune System, namely of the immune network of antibodies, from one experiment to another. Although the results are not conclusive, there is a strong indication that this adaptation is, as expected, helpful for the generation of pleasant imagery.

Figures 7 to 9 present some sample images created during these experiments and the corresponding mathematical expressions.

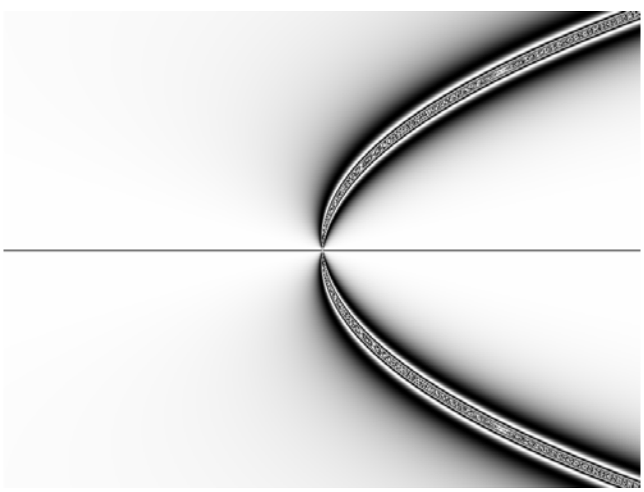

Figure 7. Image corresponding to the expression (cos(+0.55 (#(0.4,0.5,0.2)))).

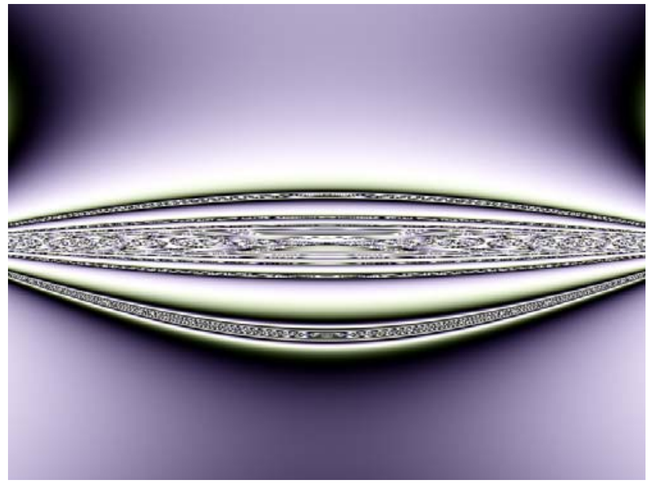

Figure 8. Image corresponding to the expression (cos(+(tan(+(- y 0.75)(/(- (cos x)(/ 0.5 2)) y))) (#(0.4,0.5,0.2)))).

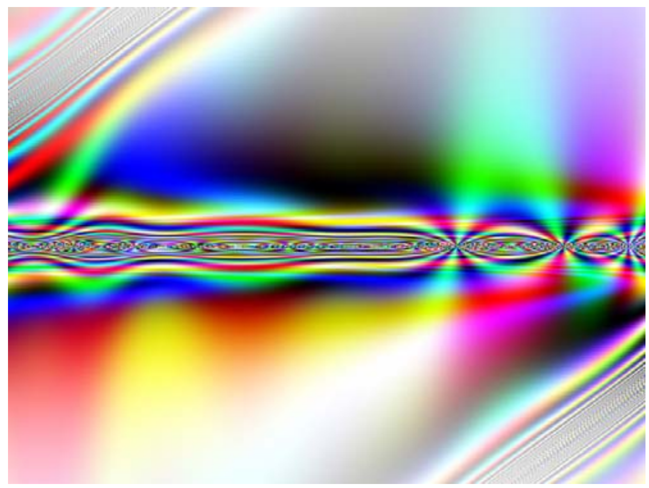

Figure 9. Image corresponding to the expression (cos(-(cos (*(#(-0.5, -0.7, -0.75)) 10)) (/(*(#(0.4, 0.5, 0.2)) (sin (- y x))) y))).

Conclusions

We have presented an interactive art generation system based on an artificial immune system mechanism. Although more tests are required, the experimental results accomplished so far are promising, demonstrating the system's ability to generate pleasant images.

One of the characteristics of artificial immune systems is their long-term memory. This may become useful for accumulating past experience and incorporating the aesthetic preferences of different users. A comprehensive set of experiments is in progress to determine the relevance of this mechanism.

The interaction mechanism is also a novel aspect of this system. The user points out interesting areas of the image, and the system determines sub-expressions which are important for the visual appearance of those areas. In conjunction with the AIS, this mechanism allows us to obtain new images having a great affinity with the selected areas.

We intend to carry out a thorough assessment of the present system, comparing it to evolutionary art tools, and to have it tested by a large number of users from different cultures.

Being, as far as we know, the first application of artificial immune systems in artistic domains, this project opens a new research line for artificial art creation.

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