University of London

6CCS3PRJ Final Year Project

2-Dimensional and 3-Dimensional Evolutionary Art Using Genetic Algorithms

Final Project Report

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Abstract

This study is about producing Evolutionary Art through the use of Evolutionary Algorithms. Evolutionary Algorithms are capable of generating artistic images from given reference images as an optimisation problem without the introduction of any prior knowledge or constraints and require little to no human intervention. Previous techniques used to generate Evolutionary Art were focused on the production of 2-dimensional artistic images from a single reference image. This study explores a method to generate 3-dimensional digital anamorphic sculptures that are rendered in a 3D environment which can produce artistic images from multiple reference images simultaneously depending on the perspective at which you view the digital anamorphic sculpture. This technique involves using the Python Image Library (PIL) to describe the digital sculpture as two 2-dimensional images viewed from specific perspectives and rendering the sculpture in 3 dimensions using the python library Vpython. Several different algorithm designs and techniques were tested and evaluated in order to find a balance between run-time efficiency and final artistic results. The final digital art pieces generated during this project were included in a survey where 14 participants evaluated the results in terms of visual appeal and recognizability.

Originality Avowal

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Patrick Whyte

April 23, 2020

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Chapter 1

Introduction

In the field of Computer Science an area of keen interest for research within Computer Graphics (CG) is Non-Photorealistic Rendering (NPR). Traditionally, the field of CG has specialized in the production of photorealistic renderings which aim to reproduce the effects of how light interacts with a scene and a lens of a camera in order to produce digital renderings indistinguishable from reality. The fundamental distinction between photorealistic rendering and NPR is that the geometric models do not need to correspond exactly to the object being modeled [23]. In fact, NPR focuses on the use of different rendering algorithms in simulating a wide variety of traditional artistic mediums such as; watercolors[9], colored pencils[16], and paint[12]. One area of NPR is Image stylization[18] which takes a reference image and is able to apply a specific artistic style such as line drawings[13], mosaics[4] or cartoon[22] to the given reference image.

Recently the use of Evolutionary Algorithms (EA) has proven to be exceedingly useful in the production of image stylized digital art. An EA is a type of metaheuristic optimization algorithm[24] that is inspired by the biological processes of evolution through mutation and natural selection. By describing the specific artistic styles as optimization problems the EAs can be used to gradually transform given reference images into digital art in the chosen artistic style. The production of this digital art through the use of EAs is called Evolutionary Art. Evolutionary Art has been favoured as it usually requires little to no human intervention in order to create the digital art.

Using EAs that require minimal human intervention to create NPR for digital art also opens the opportunity to produce high volume artistic images needed for the insatiable content requirements for fresh, provocative, eye-catching visuals to insert in online advertising and to accompany online editorial content. Providing fast, impactful and cost effective digital art for these purposes is a significant breakthrough opportunity for these industries.

This paper aims to continue the research in NPR Image Stylization, specifically in the artistic style of Pointillism. This project focuses on this process through the use of Genetic Algorithms (GA) which are a type of EA. During this project we will evaluate the performance of a GA in generating 2-dimensional digital art pieces from a single reference image and explore a novel technique to use a Multi-Objective Genetic Algorithm (MOGA) to generate 3-dimensional digital anamorphic sculptures using multiple reference images simultaneously. These digital anamorphic sculptures are composed of a collection of 3D spheres arranged in a specific way so that it is able to display the digital art generated from the multiple reference images used depending on the perspective at which you view the digital sculpture from. The final digital art pieces generated during this project were included in a survey where 14 participants evaluated the results in terms of visual appeal and recognizability.

1.1 Report Structure

This report is divided into 3 main components:

1. Contextual Overview of the Project
2. The Approach to the Development
3. Testing and Evaluation

The Contextual Overview of the Project will provide a background of the different types of artistic styles that are being replicated in this project. The report will then go into a critical evaluation of the existing literature and research papers in the area of NPR and Evolutionary art. It will go on to provide context for the motivation for this project and will explain how the work done is related to the existing work discussed during the literature review.

The Approach to Development aims to explain the software development portion of this project. This section of the report will begin by defining the problem and providing an abstract outline of the design of the specific MOGA developed for this project. It will then go into detail about the implementation of the algorithm on a code level and explain the decisions made during the development of the project.

The Testing and Evaluation section, the report will describe each of the different tests conducted on the algorithm and provide explanations to their relevance to the project. The final artistic results generated by the algorithm using a single reference image and multiple reference images will be presented and evaluated taking into consideration the answers from the survey conducted. Finally, the report will provide a conclusion for the project and outline opportunities for future work to be done in this area.

Chapter 2

Background

2.1 Pointillism

Pointillism is a specific style of art developed in the late 19th century by the artist Georges Seurat. The technique involves painting many individual distinct dots of color onto a canvas that when viewed together produce an image. Up close the individual dots in the painting can be distinguished but the technique relies on the viewers eyes to blend the dots together to form the intended image. The Painting showed in Figure 2.1 is by Georges Seurat titled “A Sunday Afternoon on the Island of La Grande Jatte” in which the artistic style of Pointillism has been used. Notice how the painting is able to illustrate an entire scene. The zoomed in section of the Painting shown in Figure 2.2 provides a closer inspection of the aforementioned painting which allows us to see the individual dots that make up the painting.

Figure 2.1: A Sunday on La Grande Jatte, Source: Georges Seurat, 1884 [20]

Figure 2.2: Zoomed in Section of Painting, Source: Georges Seurat, 1884 [20]

2.2 Anamorphic Sculptures

Anamorphic sculptures are types of sculptures that are distorted and can only be identified from a specific vantage point. Many contemporary artists have used anamorphism in the production of sculptures that require the person to view the art from a specific perspective in order to see the undistorted image. An example of this can be seen in Figure 2.3 which shows an anamorphic sculpture created by the artist Matthieu Robert-Ortis that depending on the perspective you view the sculpture it either takes the form of an elephant or two giraffes.

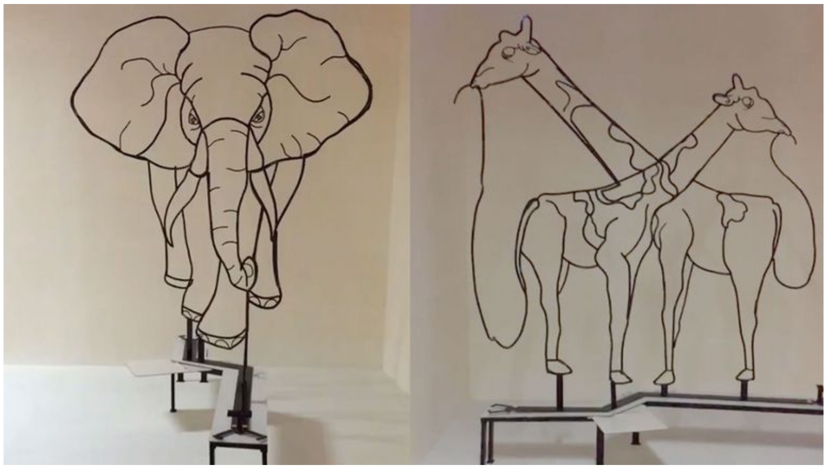


Figure 2.3: Anmorphic Sculpture, Source: Matthieu Robert-Ortis, 2017 [17]

2.3 literature Review

2.3.1 The Fly Algorithm

Research conducted by Abbood Zainab, Amlal Othman and Vidal Franck titled “Evolutionary Art Using the Fly Algorithm” has demonstrated the effectiveness of using EAs to produce digital art such as digital mosaics[4]. The Fly Algorithm is a cooperative co-evolution strategy based on Parisian evolution [8]. Typically, the Fly Algorithm had been used for the purpose of computer stereo vision where the population of flies, which can be described as an infinitely small 3D position, explores the search space corresponding to the field of view of a camera and evolve using a fitness function that determines how likely a given fly is placed on the surface of an object in order to extract 3D information from an image. However, by describing the production of digital mosaics from an input image as an optimization problem, the researchers could adapt the Fly algorithm to generate the digital mosaics as solutions to this problem without the introduction of any prior knowledge or constraint other than the input image. In this context, the flies are described as a specific “Tile” with a given position, colour, rotational angle and scaling factor that work together to generate the digital mosaics. Each Fly is given a local fitness which assesses its contribution to the global fitness. Flies that have a negative impact on the global fitness are randomly selected to be removed from the population and flies that have a positive impact on the global fitness are randomly selected to reproduce. During the evolution process the number of good flies gradually increases as the number of bad flies decreases. Eventually, the flies or “tiles” have arranged themselves in a configuration that successfully creates the digital mosaic.

2.3.2 Stanford Pointillism Digital Art

The Stanford research paper titled “Create Pointillism Art from Digital Images” demonstrates a different approach to generating digital art in the style of Pointillism from a given reference image [14]. The study investigates in depth how the artistic style of Pointillism is traditionally painted by analyzing the art work of Georges Seurat and offers an interesting technique to create digital art that closely resembles the artistic style of Pointillism. The algorithm devised by the Stanford study does not propose to use EAs but instead has chosen to develop an algorithm that generates the digital art in a three stage process. First the reference image is preprocessed in order to reduce the size and create a simpler image. It then employs the use of K-means clustering, an unsupervised machine learning technique [7], in order to generate a color palette to be used for the individual dots of the digital art. In this context, the centroids used for the K-means clustering are calculated as the mean RGB color values of all the pixels in their cluster and the cost function is described as the sum of the distances between each of the pixels RGB values and their centroids. The process converges on the K most frequent colors in the reference image. Finally, individual "dot clusters" each containing 3 individual "dots" are generated for each of the pixels in the prepossessed reference image. The individual "dots" are programmatically spaced away from one another to create the final effect.

The results of this study show that this technique is a very effective way to apply the artistic style of Pointillism onto a given reference image. However, it requires a great deal of human intervention to determine the optimal parameter values to use for each of the components of the algorithm which include but are not limited to; the number of colors to include in the pallete, dot diameters, dot cluster distances and scatter distributions in order to generate the best results. These parameters also may need to be changed and updated for each new reference image in order to produce the best results.

2.4 Motivation

The field of Evolutionary Art is an interesting research topic as it has proven effective in producing incredibly compelling pieces of digital art requiring little to no human intervention or prior knowledge other than a given reference image. The motivation for this project comes from the work developed in the research paper reviewed in the literature review titled "Evolutionary Art Using the Fly Algorithm" [4]. The research introduced a novel way of generating the digital mosaics by evolving a population of flies encoded as tiles. I was inspired by the performance of the algorithm and initially set out to implement my own EA in order to produce digital art in the artistic style of Pointillism using a similar technique. However, what was immensely interesting to me was that the flies or "Tiles" retained their coordinate positions in 3 spacial dimensions. This meant that the digital art could be rendered in a 3D environment which opened the possibility to view the digital art from differing angles and perspectives. I was motivated by the work of Matthieu Robert-Ortis, an artist who creates anamorphic sculptures that are able to change their appearance depending on the perspective at which you look at them. I had not seen any research conducted in the area about the production of Evolutionary Art using multiple reference images simultaneously and so I set out to continue the research into the performance of EAs in producing digital art and explore the potential to use multiple reference images simultaneously by creating digital anamorphic sculptures and rendering them in a 3D environment so that depending on the perspective you view them they are able to produce the digital art from one of the reference images in the style of Pointillism.

An interesting application for 3-dimensional digital anamorphic sculptures that produce artistic images from multiple reference images simultaneously depending on the perspective it is viewed, is in the area of education at: schools, universities, companies and community spaces, such as: museums and art galleries. These 3D artistic representations can be used to demonstrate complex concepts in a more entertaining and interesting format than is available at these locations today, making the learning experience more memorable and relatable, increasing retention. Imagine in schools and museums, an explanation of the universe, planets or cells in this format. For companies, imagine explaining to staff the impact of decision-making and how a problem can be interpreted from many perspectives, enhancing empathy and understanding at work. With respect to art galleries, it offers the opportunity of presenting certain art to the public in a more provocative, interactive and stimulating context.

Chapter 3

Design & Specification

3.1 Defining The Problem

The problem we are trying to solve in this project is inherently an optimization problem. As seen in the previous section, similar research has shown the effectiveness of EAs in traversing the exceptionally large search spaces created from the optimization problems defined by producing digital art from a given reference image. Reducing the complexity of the problem from exponential to linear, enables EAs to find approximate optimal solutions to NP problems [5]. Image generation through the process of translating a reference image into digital art has been described as a special case of the set cover problem which is NP-Complete [4].

This paper aims to continue the research done on the use of EAs in finding approximate solutions to these problems. The main objective of this project is to produce digital art in the artistic style of Pointillism from a given reference image and explore a novel way to use a Multi-Objective Genetic Algorithm (MOGA) to translate multiple reference images into a 3 dimensional digital anamorphic sculptures that can simultaneously illustrate the digital art for each of the given reference images depending on the perspective the sculpture is viewed.

3.2 Project Requirements

In order to produce a successful program for this project a set of requirements were devised. These requirements were used to provide a better idea of how to approach the Software Development portion of the project. After careful consideration into each of the components of the project (Performance, Artistic Result, and User Experience) the following basic requirements were defined.

- Performance
  - The program must be able to produce digital art using a wide range of reference images varying in size and complexity.
  - The program must be able to produce digital art using at least two reference images simultaneously.
  - The program must be able to produce a satisfactory result in a reasonable amount of time while also allowing for further optimization if kept running.
- Artistic Result
  - The digital art produced must be recognisable and visually appealing.
  - The digital art produced maintains the characteristics of the intended artistic style of Pointillism.
  - The digital anamorphic sculpture produced using multiple reference images must be able to successfully display the digital art from each perspective.
- User Experience (UX)
  - The digital anamorphic sculptures must be able to be rendered in 3D.
  - The user must be able to view the progression of the digital anamorphic sculptures over the generations.
  - The user interface should provide simple controls for the user allowing them to rotate the digital anamorphic sculptures to change the perspective.

3.3 Design Overview

For this project, the approach that was chosen to drive the optimization was designed around a classical Multi-Objective Genetic Algorithm (MOGA). In a Genetic Algorithm a population of possible solutions to an optimization problem are iteratively evolved towards better solutions by comparing how close each one is to the objective. In the context of this project a solution to the optimization problem is the image produced by the digital sculpture from a specific perspective. The objective is to approximate the reference image as much as possible. A MOGA was necessary for this project because each reference image used for the creation of the digital sculptures added a new objective for the Genetic Algorithm to optimize for simultaneously.

In this project, specific individuals in the population are called “Organisms”. Each Organism has a collection of “Genes” which are used to produce a single shape on the canvas. A Gene is composed of 7 elements that allow it to encode the information to produce a single shape in the 3D environment. These elements include the x, y and z coordinate values for the position, the R, G, and B values for the color and the diameter for the size. Figure 3.1 is an example of an image produced by an initial Organism from a specific perspective to provide an illustration of the relationship between the Organism and its Genes.

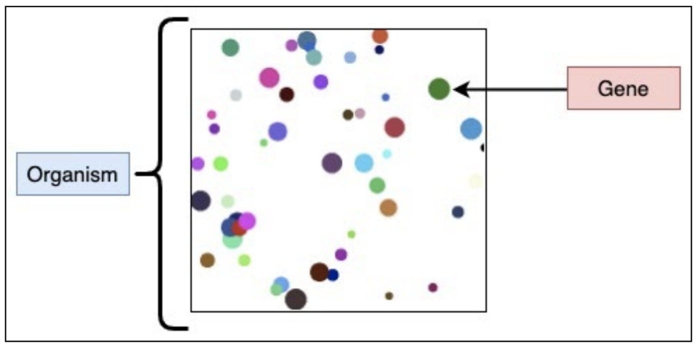


Figure 3.1: Organism and its Genes

The relationship between an Organism and its Genes is also shown in class diagram for this project which can be seen in Figure 3.2.

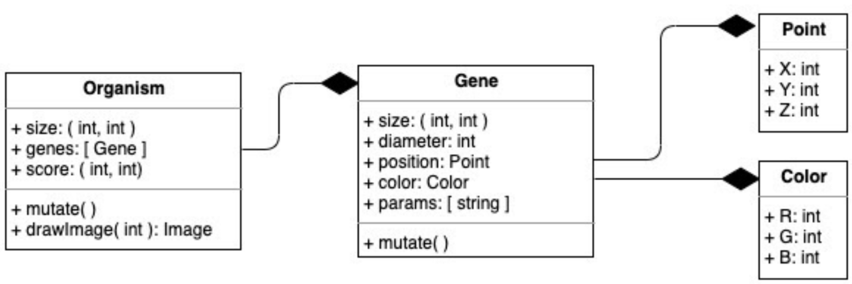


Figure 3.2: Class Diagram

The first step of the MOGA is to create an initial “Parent” Organism with a set of randomly generated Genes. This Organism is evaluated and given a score for each of the objectives. This first Organism is expected to have a poor score for each of the objectives but it provides a starting point to commence the evolution process. The evolution process can be broken down into 3 main components: Creation, Mutation and Selection. The Creation component uses the Parent Organism to generate a new population of Child Organisms. The Mutation component is used to introduce variation within the population of Organisms. The mutations themselves occur on the Gene level where each Gene of the Organism has a predetermined percentage chance of mutating (mutation rate). When a specific Gene mutates it changes the shape it creates and these small changes alter the image produced by the Organism creating the variation within the population. Once each of the Organisms have mutated we go into the final component of the evolution process, Selection. Selection evaluates the performance of each of the Organisms in the new population to each of the objectives and finds the Organism that performs the best overall. This Organism is selected to be the Parent Organism for the following generation and the whole evolution process is repeated. A flow diagram of this process is shown in Figure 3.3.

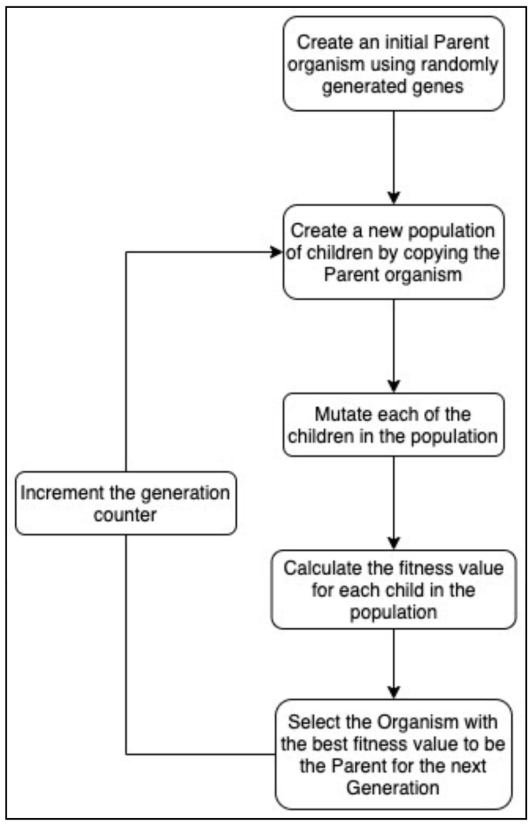


Figure 3.3: Flow Diagram

Typically, Genetic algorithms incorporate another component called “Crossover”. This component normally involves combining the data from two separate Parent solutions together in some way in order to create a new Child solution. This component is an effective way to further introduce variation into the population as well as potentially improve the performance of the children in each generation by combining the best data from the two parent solutions. However, for this specific project the Genes of the Organism are all heavily dependent on each other. The Genes rely on the other Genes around them in order to optimize themselves to produce the best results. One example of this is when Genes take advantage of the cover other Genes produce in order to become a color in a position that improves the accuracy for one reference image but would hinder the performance of another if it was not covered. Whichever way we combine the Genes from two separate Organisms to create a new child Organism the result is almost always worse off and so a crossover method was not included in the implementation of the algorithm.

Chapter 4

Implementation

In this section I will review each step of the MOGA outlined in the design overview section of the report. I will provide a detailed description of how each of the specific components were implemented on a code level and explain the decision-making process during the development of the project. I will also point out key design features of the Graphical User Interface (GUI) and explain their function in creating a positive User Experience (UX).

4.1 The Genetic Algorithm

Generating The Population

To create the population of organisms for each generation, the algorithm uses the best Organism from the previous generation (or the initial Organism if it is the first generation) as the "Parent" Organism. A predetermined population size is used to calculate the number of "Child" Organisms to create each generation. To create each Child Organism, a deep copy of the Parent Organism is created. A deep copy means that, in addition to creating a copy of the Organism object itself, it also creates a copy of each of the Gene objects associated with the Parent Organism object. This is done so that changes made to the Genes through mutations do not affect the Parent Organism. The Child Organism is then mutated and given a new score for each of the reference images to evaluate how the mutations affected the images produced by the Child Organism. In order to improve the efficiency of this algorithm the Python multiprocessing module is used to fully take advantage of the multiple processors on a given machine. The Pool object offers a convenient way of paralleling the execution of the function, greatly improving the time performance of the algorithm. The number of worker processes to use for the pool object is calculated by the number of available cores on the machine - 1.

Mutation

When an Organism mutates, each Gene has a percentage chance of mutating. To decide which Genes will mutate, a random sample is taken from the collection of Genes. The sample size is calculated by multiplying the mutation chance (0.05) by the number of Genes. This is statistically equivalent to looping through all of the Genes individually and is significantly faster. To add variation to the sample sizes for each of the Organisms, the sample size has a standard deviation of 1. Each Gene in the mutation sample is mutated. The code snippet shown in Figure 4.1 shows the mutation method for a specific Gene.

```python
def mutate(self):
    # Decide which variable will be mutated
    mutation_type = random.choice(self.params)

    # Mutate the variable
    if mutation_type == "diameter":
        if BOUND_GENE_SIZE:
            self.diameter = min(max(5, int(round(random.gauss(self.diameter, 2)))), 15)
        else:
            self.diameter = max(5, int(round(random.gauss(self.diameter, 2))))

    elif mutation_type == "pos":
        x = min(max(0, int(round(random.gauss(self.pos.x, 5)))), self.size[0])
        y = min(max(0, int(round(random.gauss(self.pos.y, 5)))), self.size[1])
        z = min(max(0, int(round(random.gauss(self.pos.z, 5)))), self.size[0])
        self.pos = Point(x, y, z)

    elif mutation_type == "color":
        r = min(max(0, int(round(random.gauss(self.color.r, 20)))), 255)
        g = min(max(0, int(round(random.gauss(self.color.g, 20)))), 255)
        b = min(max(0, int(round(random.gauss(self.color.b, 20)))), 255)
        self.color = Color(r, g, b)
```

Figure 4.1: Mutation method for a Gene

When a specific Gene mutates, one of the parameters of the Gene (Position, Diameter, Colour) is selected to be mutated. In each case, the individual values for those parameters are shifted by generating a new value from a gaussian distribution with a parameter specific standard deviation where the mean is the current value. Preliminary tests were conducted to find the standard deviations that worked best for each of the parameters. Setting the standard deviation too high would cause the mutations to be too dramatic reducing the optimization to essentially trial and error. Instead, the standard deviation was set to the smallest reasonable size to ensure that the mutations behave as small and incremental changes to allow the parameters to gradually move towards more optimal values. The diameter of the Genes was given an upper limit on its mutations to prevent the size of the Genes from becoming too big. Preliminary tests indicated that when the diameter of the Genes was left unbounded it no longer produced digital art in the intended artistic style of Pointillism. During mutation the Organism also has an 80

Drawing an Image From an Organism

The function to produce an image from an Organism uses the imageDraw module from the Python Image Library (PIL). First, a completely white image is created and used as a canvas to draw the individual Genes. In order to draw the image produced by the Organism from a desired perspective we take advantage of how the PIL module draws shapes onto images. Shapes are drawn by calculating which pixels are within the area of the defined shape and setting the color of those pixels to the desired color. This means that when a shape is drawn, any previously drawn shapes (and the original image) in the same area are covered up by the newly drawn shape. Using this principle, we are able to draw the Organism from a specific perspective. Figure 4.2 offers a simple representation of the 3D environment in which the Organism is rendered. The Organism (shown as the collection of blue spheres) is contained within an imaginary cube with dimensions equal to the size of the reference image. Each perspective can be thought of as looking at the Organism from one of the faces of the cube.

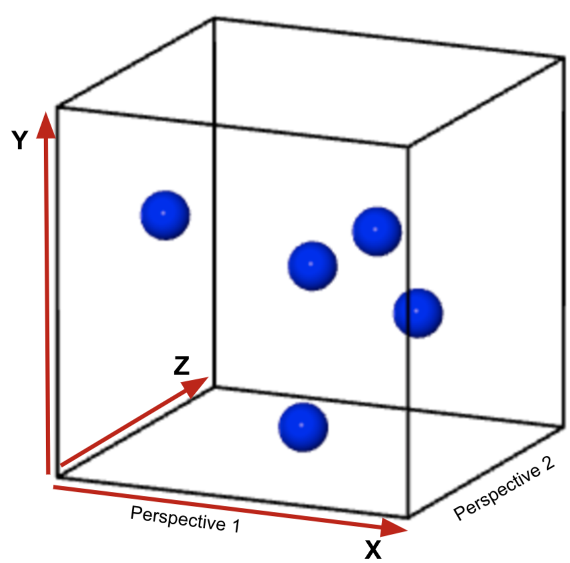


Figure 4.2: Perspective Diagram

By sorting the Organism's Genes by a desired coordinate value, the Genes further away from the camera position are drawn first and Genes closer to the camera (in front of them from this perspective) are drawn on top of them. For *Perspective 1* and *Perspective 2* in Figure 4.2 we sort the Gene's by their Z and X coordinate values respectively. When defining the position of the Genes to draw on the canvas it is also important to replace the relevant coordinate values. For *Perspective 1* the image can be drawn normally by using the X and Y coordinates. However, for *Perspective 2* the X coordinate value is replaced with the Z coordinate in order to adjust for the rotation of the Organism.

Score Calculation

For the algorithm to run efficiently it was important to be able to evaluate how close the Organism is able to approximate the reference images as fast as possible. To achieve this, a method was devised to calculate a score of how different the images produced by the Organism are from their target reference images without having to render the Organism in 3D which greatly increases the run time. Similar to how the global fitness was calculated in the research paper using the fly algorithm referenced in the literature review, the technique chosen to calculate the score of the Organism uses the pixel-by-pixel Sum of Absolute Errors (SAE) between the two images. This approach is also known as the Manhattan distance [4]. By minimising the score, the Organism is able to produce an image that closely resembles the target reference image. The score can be described by the following equation where *org* is the image produced by the Organism from a specific perspective and *ref* is the target reference image.

$$SAE(org, ref) = \sum_i \sum_j |org(i,j) - ref(i,j)| \tag{4.1}$$

The score is calculated by creating a difference image from the image produced by the Organism from a specific perspective and the reference image using the PIL module image-Chops. A difference image is described in the PIL documentation as the 'absolute value of the pixel-by-pixel difference between the two images'[3]. The difference image is then converted into a numpy array to calculate the sum of the pixels in the difference image. The Organism's score is also used to calculate how accurate the images are to their target reference images as a percentage. This accuracy is used to give the user an understandable numerical metric of how close the digital art produced by the Organism is to the reference image in each generation. The equation below describes how the accuracy percentage is calculated where l and w are the length and width of the reference image in number of pixels respectively.

$$Accuracy = 100 - \frac{\left(\frac{SAE(org,ref)}{255*100}\right)}{l*w*3} \tag{4.2}$$

Calculating Fitness

Each generation the best Organism in the population is selected to be the Parent Organism for the following generation. The best Organism is the one that is able to minimise the sum of the scores for each of the reference images used added to the total number of Genes the Organism has multiplied by a weight. The number of Genes is multiplied by the weight so that it has a significant effect on the final fitness value. The weighted number of Genes is included in the fitness value to encourage the Organisms to use the fewest amount of Genes possible. There is an incentive to use less because fewer Genes require fewer computations making the algorithm run significantly faster. It also produces more interesting results where the same Genes are used to optimize for multiple reference images simultaneously.

In the context of this project, each of the score values for the reference images are their own objective, to be optimized for, as well as minimising the total number of Genes. This is why a MOGA was used for this project. A MOGA is able to combine all these objectives into a single fitness function. The Organism that is able to minimise this fitness function the most, is therefore the best within the population. The fitness function can be described by the following equation where N is equal to the number of reference images used, *SAE(x, y)* is the equation for the score defined in in the previous section, *org* is the image drawn by the Organism from perspective i, *ref* is the ith reference image, G is the number of Genes the specific Organism has and w is a weight.

$$Fitness = \left(\sum_{i=1}^{N} SAE(org_i, ref_i)\right) + G*w \tag{4.3}$$

Visualizing the Evolution Process

Figure 4.3 demonstrates how the Organism “evolves” from an initial random set of Genes using gradual improvements over several generations.

It must be stated that the level of accuracy does not directly correlate to how visually appealing or recognizable the digital art is, but rather provides a numerical metric to how similar the digital art produced by the Organism is to the intended reference image in terms of pixel-per-pixel difference.

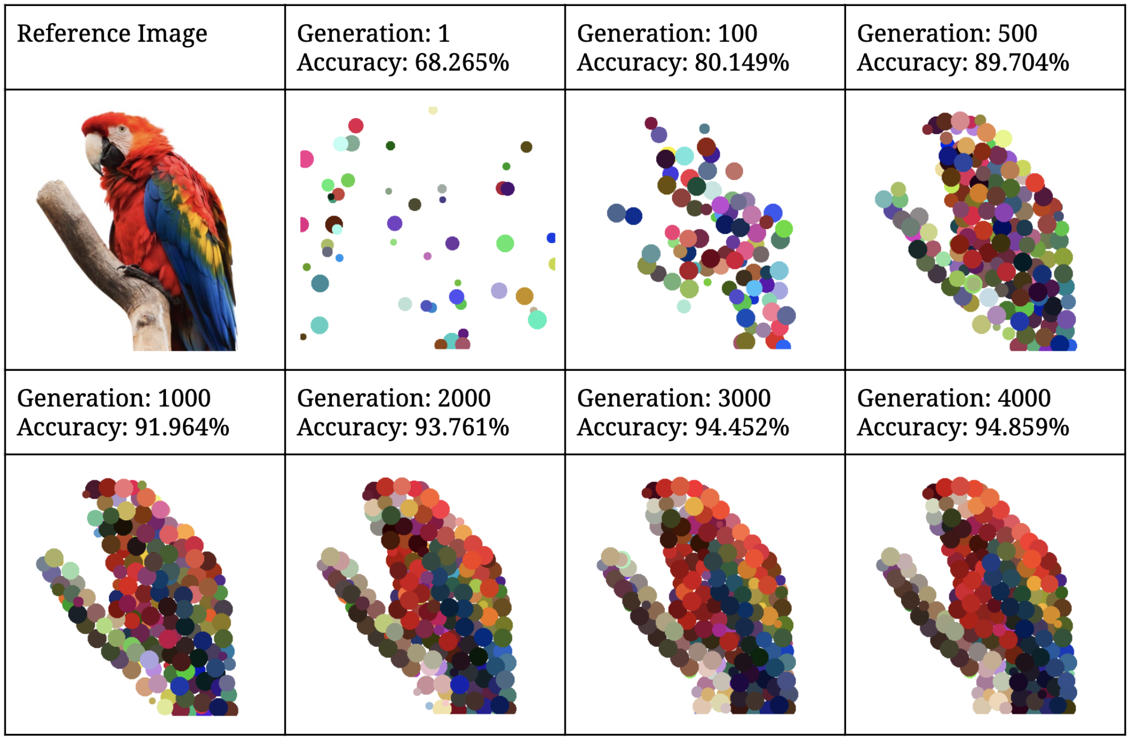


Figure 4.3: Evolution Process

4.2 User Experience

Rendering in 3D

In order to create the user interface for this project the python library Vpython was used. Vpython includes a 3D Graphics module called Visual which is used to render the digital art in 3D. In order to render the digital art produced by the Organism in 3D as best as possible several changes were made to the scene. The default directional lighting was replaced with a bright ambient light in order to remove the shadows cast on to the spheres. The increased brightness of the ambient light also allowed for the colors of the Genes to be represented accurately. To avoid issues caused by varied perspectives based on where the user positioned the camera, the "field of view" (FOV) of the camera was narrowed dramatically in order to produce an orthographic projection of the digital art making it significantly easier for the user to find the correct position to place the camera in order to view the digital art from a desired perspective.

Graphical User Interface

An annotated screenshot of the Graphical User Interface is shown in Figure 4.4. The GUI was designed to be as simple as possible to make it easy for the user to view and manipulate the

3D rendered Organism while also providing plently of interesting visual information about the current Organism.

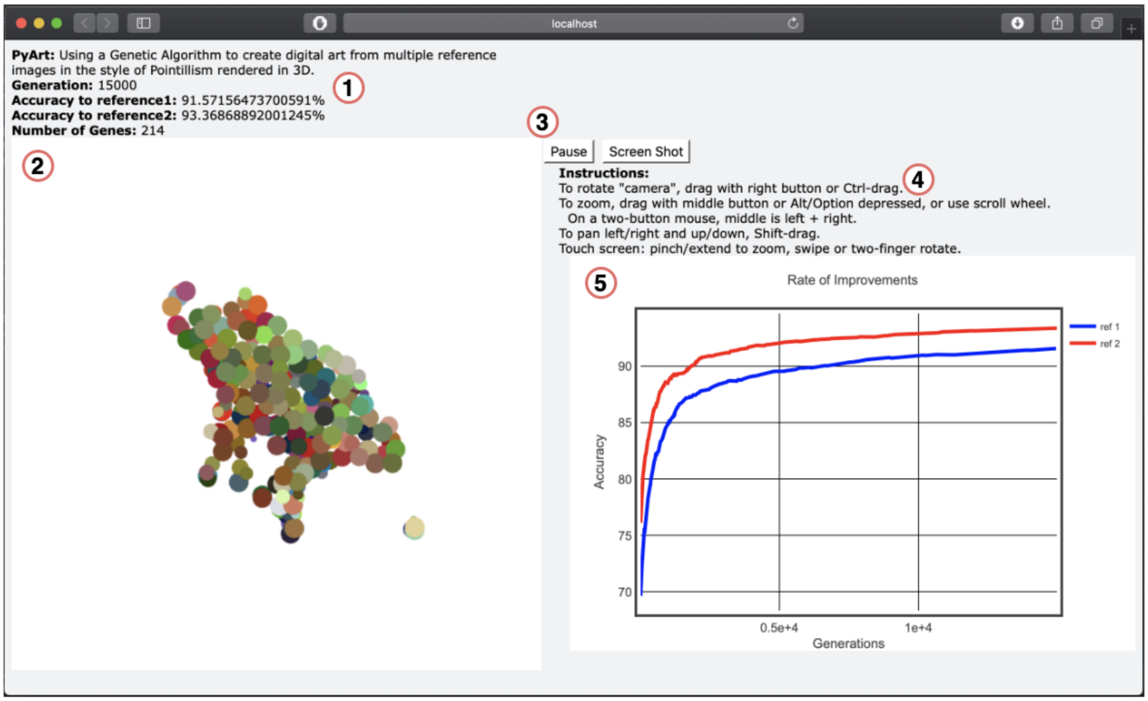


Figure 4.4: A screenshot of the Graphical User Interface (GUI)

1. The Live Display Counters: Provided the user with relevant realtime information about the digital art being displayed such as the: current generation, accuracy to each of the reference images and the total number of Genes.

2. The 3D Scene: Used to render the Organisms and display the digital art. It allows the user to control the camera in order to change the perspective.

3. Buttons: The “Pause” button allows the user to pause and run the execution of the algorithm on a specific generation to allow them to view the digital art uninterrupted. The “Screen Shot” button allows the user to take a picture of the digital art and save it directly to their downloads folder.

4. Instructions: The instructions provide a guide on how to control the camera for the 3D scene.

5. The Graph: Displays the real time rate of improvement of the digital art being generated. Providing the user with additional information that may be helpful with understanding how the genetic algorithm is able to approximate the given reference images.

Chapter 5

Professional Issues

As with any software development project it is crucial to ensure that we are following the guidelines set out in the Code of Conduct & Code of Good Practice issued by The British Computer Society. It is absolutely necessary that we are aware of these codes and apply their principles during the development of this project. These codes were followed and carefully considered when deciding which reference images to use for the production of the digital art in this project. The reference images chosen were selected as they are uncontroversial and do not infringe on any data protection laws. The reference images were properly cited to give credit and recognition to the artists and photographers that created the images where needed. This project has also included a survey where participants provided answers to questions about the digital art created during this project. The proper steps were taken in order to ensure that the data collected about the participants was stored securely and that none of the data collected during the survey was distributed to any third-parties without prior consent from the participants. The survey questions were designed to be as unbiased as possible and the participants were able to answer the survey questions anonymously.

Chapter 6

Experimentation

6.1 The Reference Images

		
Reference Image 1: A rainbow macaw. Used to see how the algorithm performed on an image with a wide range of multiple unique colors.	**Reference Image 2:** A tree frog. Used to see how the algorithm performed on an image with multiple shades of the same general color (green).	**Reference Image 3:** A self portrait of Georges Seurat. Used to see how well the algorithm was able to approximate a human face.
		
Reference Image 4: A cactus. Used to see how the algorithm performed with small subtle details such as the spikes and shadow effects.	**Reference Image 5:** A smiley emoji. Includes very simple shapes and few varying colours. Used as an “easiest case scenario” image.	**Reference Image 6:** The KCL Logo. Includes very complex shapes, small details and multiple contrasting colors. Used as a “hardest case scenario” image.

Figure 6.1: Reference Images ref.1[15], ref.2[11], ref.3[19], ref.4[21], ref.5[10], ref.6[1]

6.2 Preliminary Tests

Before the initial tests a few preliminary tests were conducted in order to find the implications of implementing certain features and evaluate the feasibility of using different techniques for the production of digital art for thi project. One of these preliminary tests was to analyze how the digital art produced by the algorithm would look when the sizes of the Genes were unbounded. This meant that the Genes could increase to any size during the evolution process. Figure 6.2 illustrates the digital art created using reference image 3 and unbounding the Gene size. The Genes favoured an increased size in order to approximate a larger area of the target image. The results produced images that no longer kept the intended art style of Pointillism and so an upper bound on the size of Genes was created.

Figure 6.2: Digital Art Generated with Unbounded Gene Sizes

Another feature that was tested during the preliminary tests was the use of alpha transparency in the images. The color values were updated to include RGB and A (alpha-transparency) values. Genes could mutate the alpha transparency value in order to become more opaque or transparent. The initial intention was to add another variable for Gene expression that the algorithm could use in order to create more interesting results. However, this feature was not implemented further as it required a new complicated function in order to draw each Gene onto the canvas which greatly increased the number of computations required each generation dramatically slowing down the execution of the program.

6.3 Using a Single Reference Image

An Initial test was conducted on a simplified version of the algorithm. This algorithm generated 2 dimensional images to illustrate the digital art and only used a single reference image at a time. This test was done in order to analyze the results using different basic shapes (Circles, Squares and Triangles) for the Genes and examine how well each of the shapes performed at creating digital art in the style of Pointillism. By using the simplified algorithm that only used a single reference image, it also provided a "best case scenario" on the performance of the genetic algorithm in generating digital art for each of the reference images. These digital art pieces could be used to compare the results of the digital art produced by the main algorithm that would be using multiple reference images simultaneously.

6.3.1 Control Variables

The initial tests included the following control variables:

- Population Size: 50
- Mutation Rate: 5%
- Add Gene Chance: 80%
- Remove Gene Chance: 70%
- Initial Number of Genes: 50
- Maximum Generations: 4000

6.3.2 Results

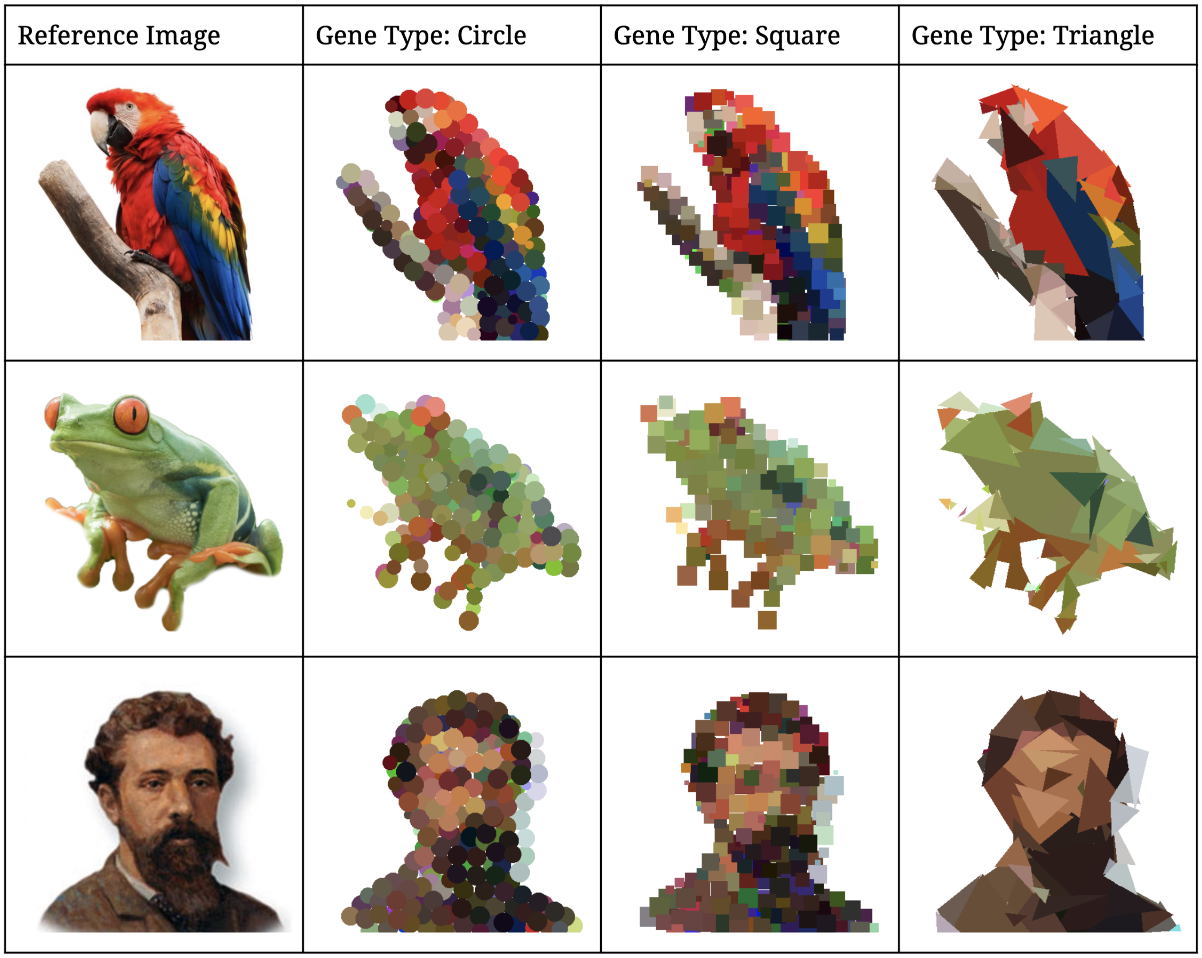


Figure 6.3: The Digital Art Generated Using the First 3 Reference Images

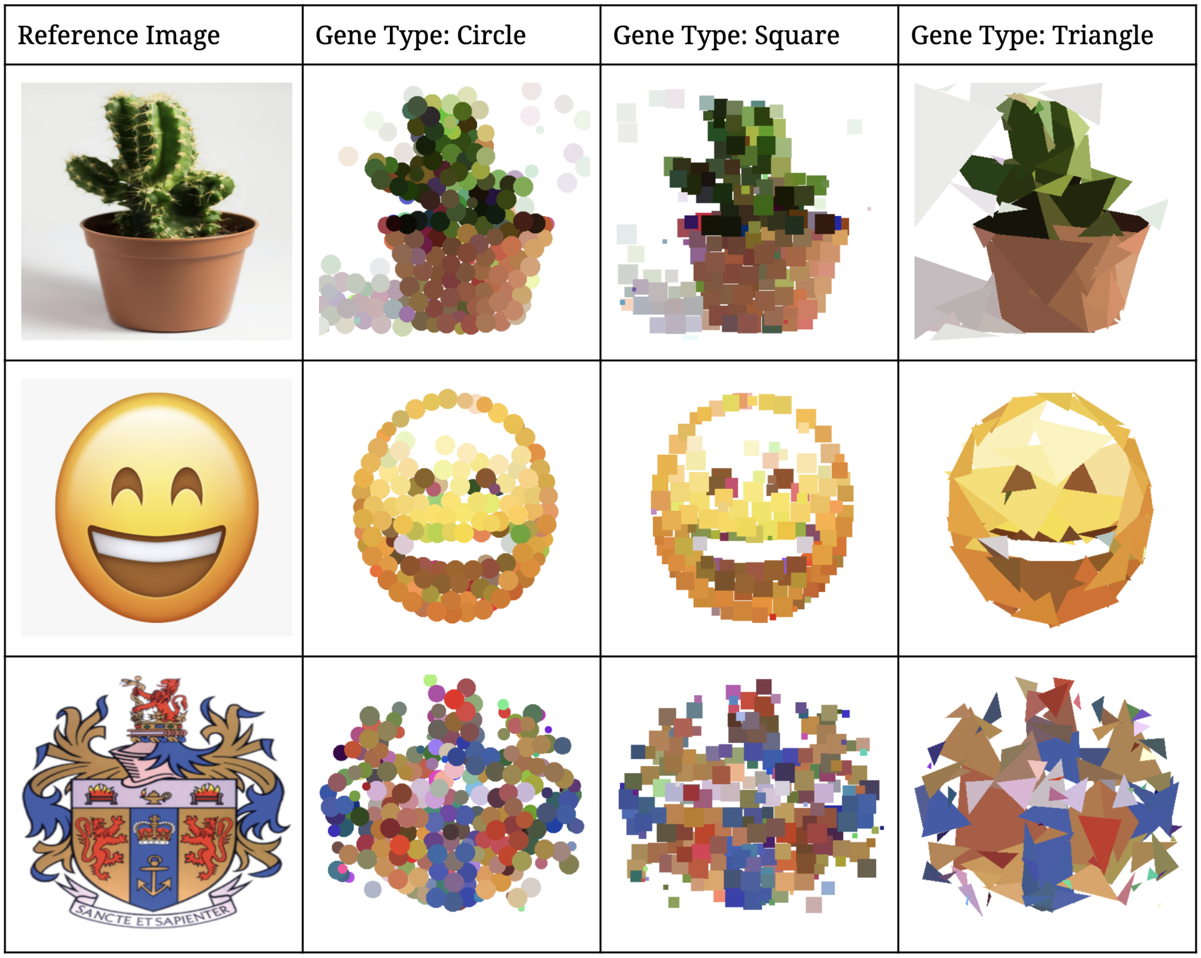


Figure 6.4: The Digital Art Generated Using the Last 3 Reference Images

As well as evaluating the appearance of the digital art produced during the preliminary tests, the final gene count and final accuracy of the Organisms were also analysed in order to obtain a better understanding of the effectiveness of using each Gene type. Final Gene count (which can be seen in Figure 6.6) was a decisive variable because Organisms that could produce digital art using fewer genes required less computations each generation which allowed the algorithm to run significantly faster. As seen in Figure 6.6, Organisms using the triangle Gene type were able to use far fewer total Genes than the Organisms using the circle and square Gene types. Despite this fact, Figure 6.5 shows that Organisms using the triangle Gene type were also able to achieve the highest level of accuracy for each of the reference images, but they lacked the ability to produce digital art that kept within the intended art style of Pointillism. In every case, using the circle Gene type required less Genes than using the square Gene type. Although both the circle Gene type and square Gene type managed to maintain the Pointillism art style, Figure 6.5 shows that the square Gene type was outperformed by the circle Gene type in terms of accuracy for each of the reference images. After reviewing the results from this initial test, it was decided that the circle Gene type would be used for the 3D implementation of the algorithm.

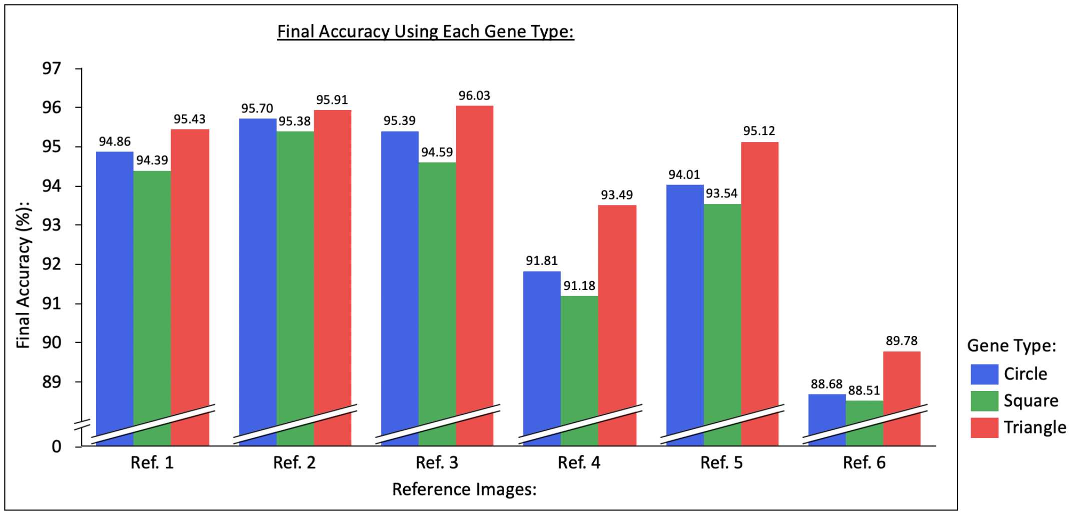


Figure 6.5: Final accuracy of digital art for each reference image using different gene types

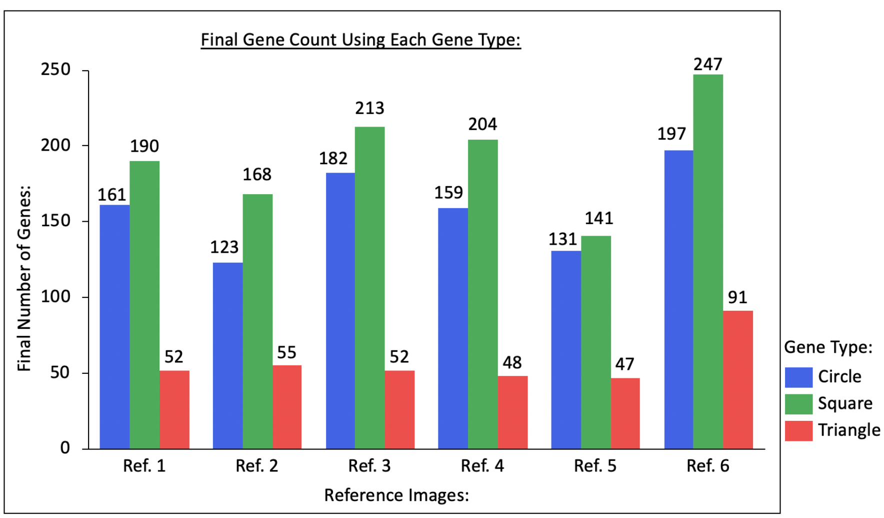


Figure 6.6: Final Gene count of digital art for each reference image using different gene types

6.4 Using Multiple Reference Images

The following section explains the experimentation performed for the main algorithm implemented for this project. Organisms are now rendered in a 3 dimensional environment and depending on their perspectives they are optimizing for different reference images.

6.4.1 Visualizing the 3D Digital Anamorphic Sculptures

Figure 6.7 illustrates how the digital art produced by the Organism can be rotated in order to switch perspectives to view the different artistic images.

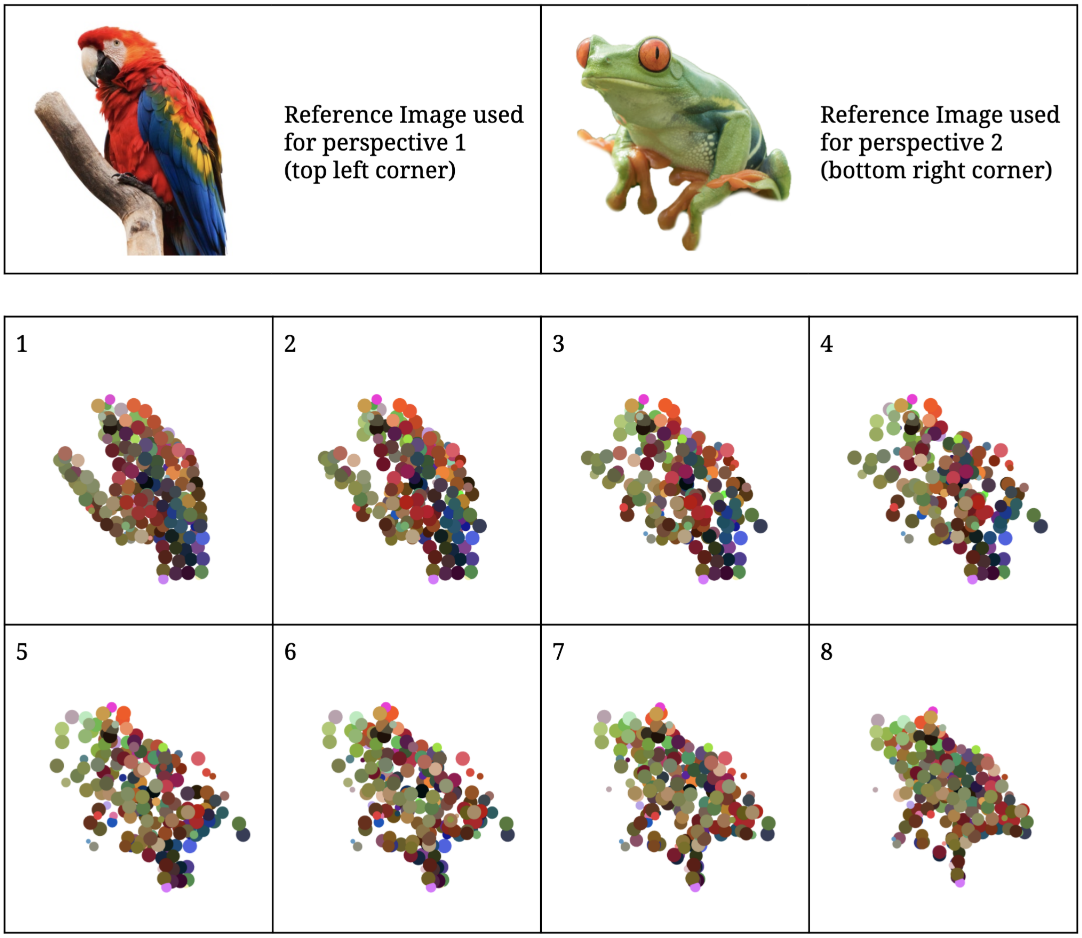


Figure 6.7: Illustration of a rotating digital anamrophic sculpture

Starting from perspective 1 (top left corner) the Organism is slightly rotated to the right until the camera is in the position to view the Organism from perspective 2 (bottom right corner). Figure 6.8 offers a "top-down" view of the Organism to help demonstrate the perspectives relative to the Organism.

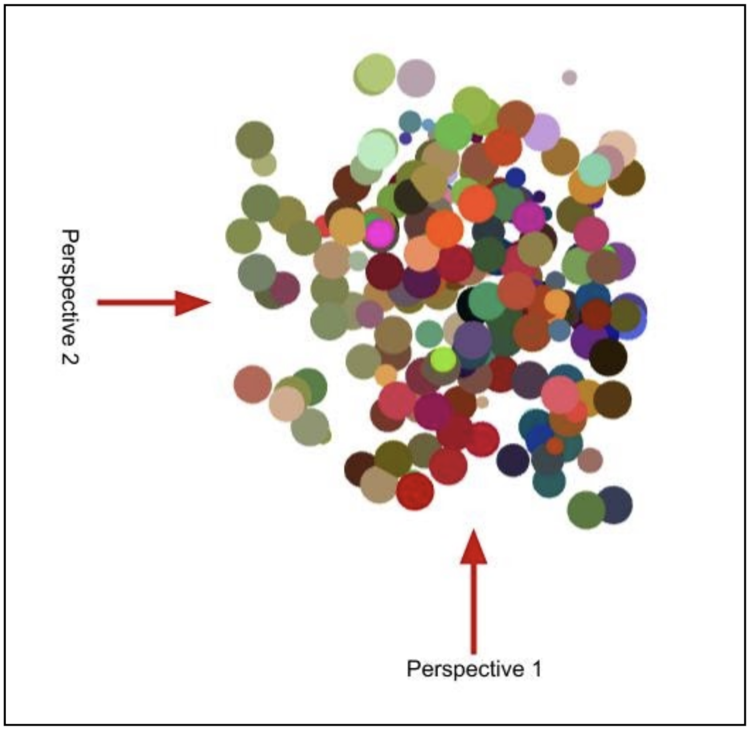


Figure 6.8: A top-down view of an Organism

6.4.2 Control Variables

The following control variables were used for the final set of tests on the performance using multiple reference images:

- Population Size: 10
- Add Gene Chance: 80%
- Remove Gene Chance: 70%
- Initial Number of Genes: 50
- Maximum Generations: 15,000

Due to the increase of computations required to produce the digital art from 1 reference image to 2, the size of the population was reduced to 10. This allowed the algorithm to run faster however, the rate of improvement of each generation was slightly reduced. As a result of this, and the increased complexity of optimizing the digital art for two reference images simultaneously, the number of generations was increased to 15,000 to ensure the algorithm had enough opportunities to produce valid results.

6.4.3 Mutation Rate

One of the main features that affect the performance of Evolutionary Algorithms is the mutation rate. In this project, the mutation rate defines the percentage chance each gene has of mutating in a given Organism. It is imperative to practically all evolutionary algorithms to find a mutation rate that is able to balance the principles of Exploration and Exploitation. Exploration takes advantage of a high mutation rate allowing the algorithm to explore all of its limitations[6]. The high mutation rate creates a diverse population which increases the probability of finding Organisms with successful Genes within its population. Exploitation takes advantage of a lower mutation rate to allow the algorithm to exploit the Organisms with successful Genes found within the population. Setting the mutation rate too high becomes counterproductive because the Organism is unable to keep successful genes from mutating. Setting a mutation rate too low may cause the algorithm to fall into a local optimum, preventing it from finding the best possible solution. One strategy is to use variable mutation rates that start high and gradually decrease over the generations. This allows the algorithm to explore the limits of the solution space in the beginning and then once it has found a diverse set of successful genes the mutation rate decreases allowing it to make smaller incremental changes to optimise the genes further, with a lower risk of changing the successful genes.

In order to find the best mutation rate to use for this project a series of tests were conducted using different fixed mutation rates (5%, 10%) as well as a variable mutation rate (starting at 10% decreasing by 1% every 500 generations). Due to the random nature of the genetic algorithm each of the different mutation rates was tested 3 times in order to calculate an average. For these tests, the same reference images (Reference Images 1 and 2) were also maintained as control variables in order to ensure that the results of the tests were only dependent on the mutation rate.

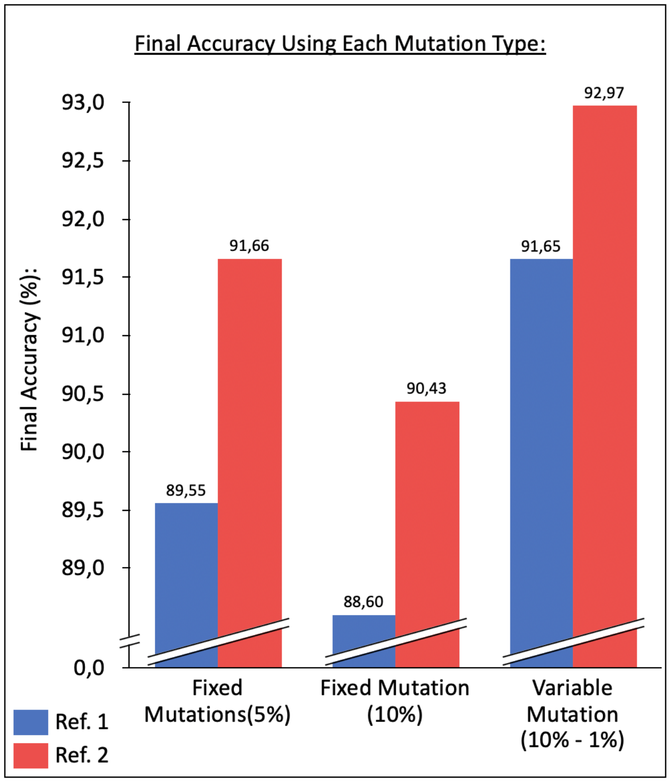


Figure 6.9: The average final accuracy using each mutation

Figure 6.9 shows the effect different mutation rates had on the final accuracy of the digital art produced by the Organism after 15,000 generations. Between the fixed mutation rates, the 5% mutation rate on average performed better than the larger 10% mutation rate which demonstrates how the increased mutation rate can be counterproductive. However, Figure 6.9 clearly shows that the variable mutation technique on average produced the most accurate results therefore, the variable mutation rate was kept as a new control variable for the final tests.

6.4.4 Results Using 2 Reference Images

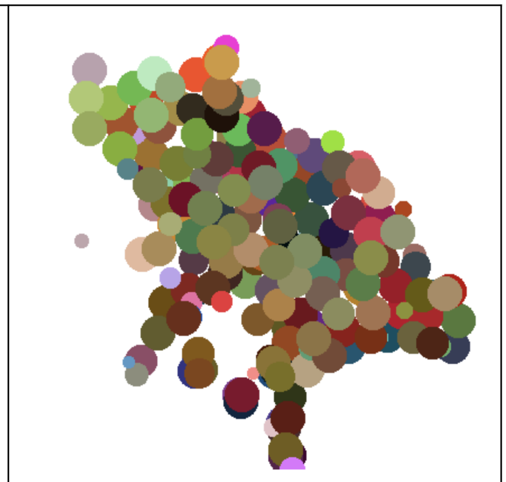
	
Perspective 1 Target: Reference Image 1 Final Accuracy: 91.57156%	Perspective 2 Target: Reference Image 2 Final Accuracy: 93.36869%

Figure 6.10: Results using reference images 1 and 2 simultaneously

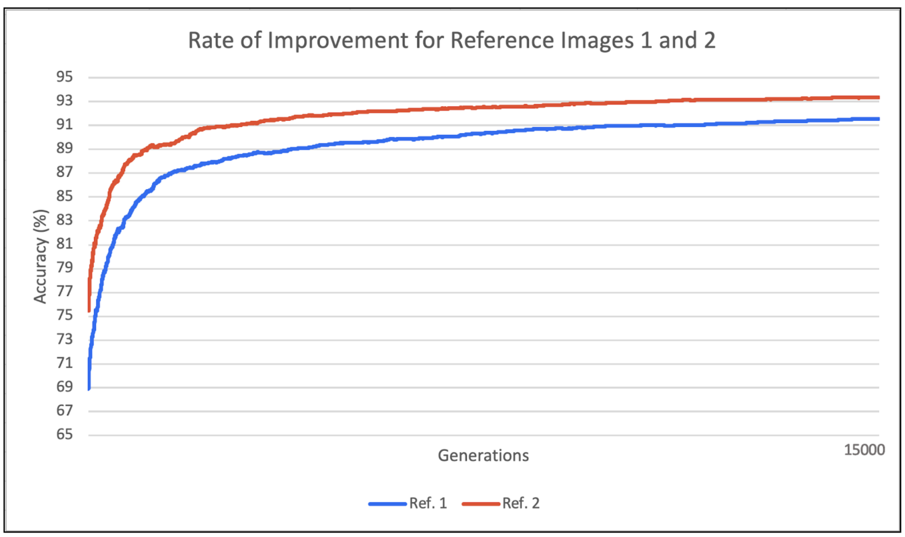


Figure 6.11: Improvement to accuracy over the generations for reference image 1 and 2

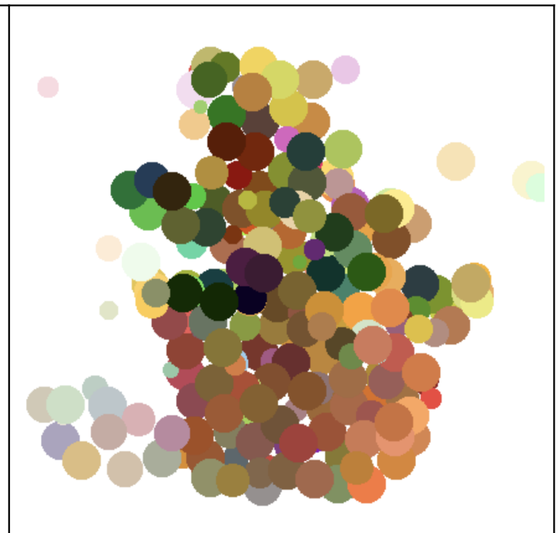
	
Perspective 1 Target: Reference Image 5 Final Accuracy: 90.10710%	Perspective 2 Target: Reference Image 4 Final Accuracy: 87.42828%

Figure 6.12: Results using reference images 4 and 5 simultaneously

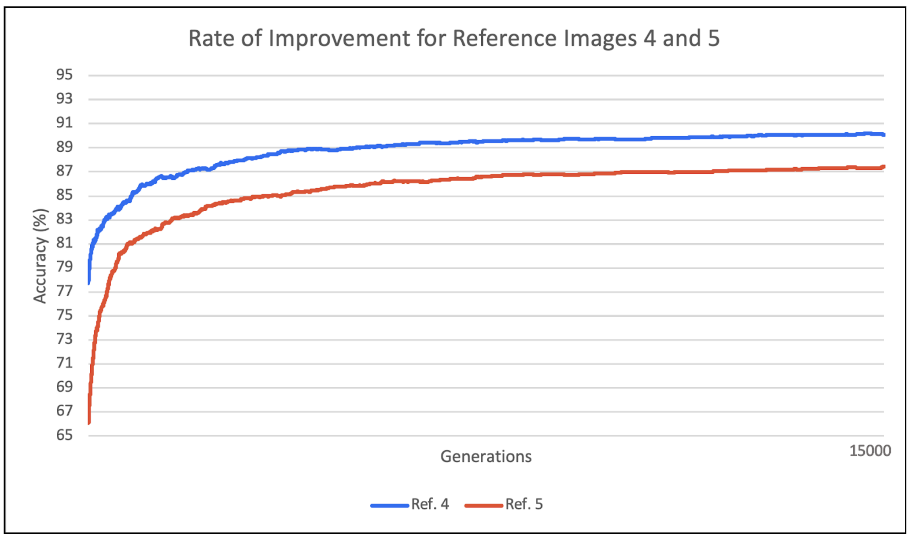
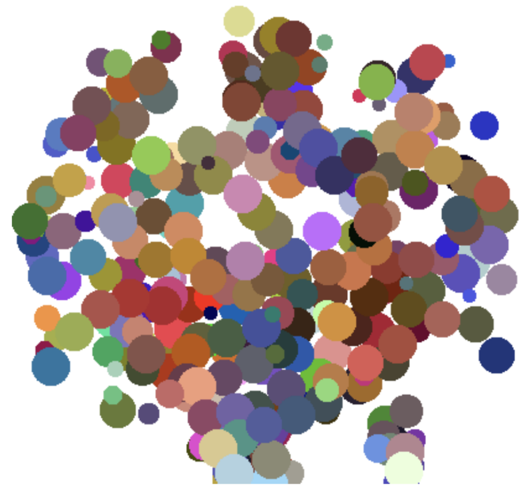


Figure 6.13: Improvement to accuracy over the generations for reference image 4 and 5



Perspective 1	Perspective 2
Target: Reference Image 3	Target: Reference Image 6
Final Accuracy: 90.87483%	Final Accuracy: 84.67456%

Figure 6.14: Results using reference images 3 and 6 simultaneously

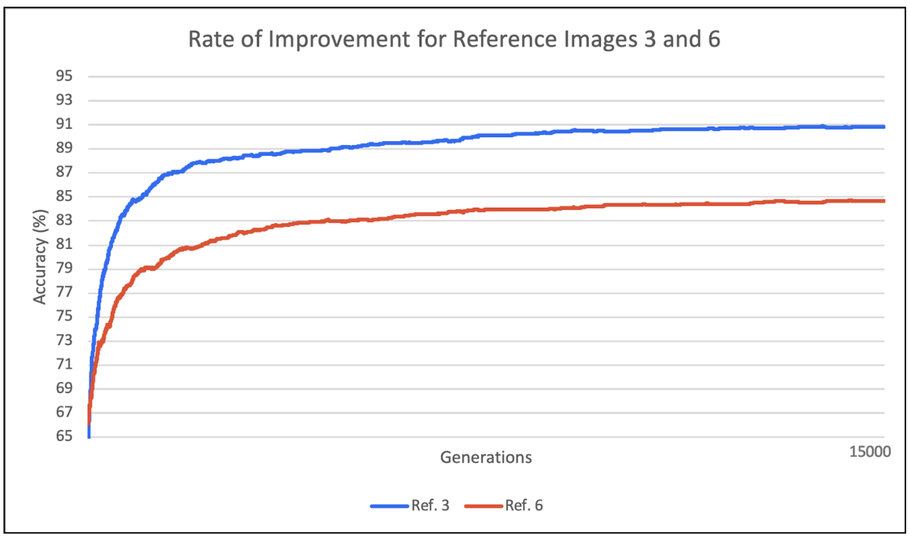


Figure 6.15: Improvement to accuracy over the generations for reference image 3 and 6

6.4.5 Results Using 3 Reference Images

To create an Organism that could optimize for three reference images the same technique used to create the second perspective described in section 4.1 under Drawing an Image From an Organism was used to create the third perspective positioned as the “top-down” view of the Organism.

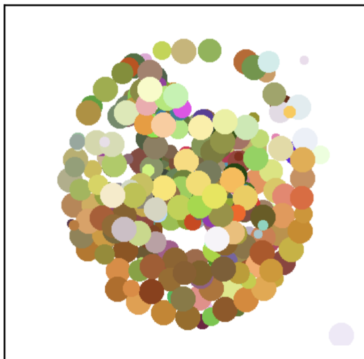
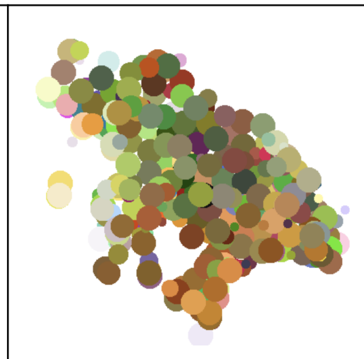
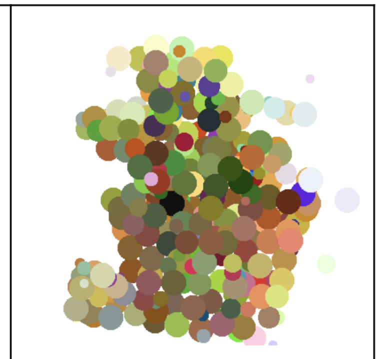
		
Perspective 1 Target: Reference Image 5 Final Accuracy: 89.66462%	Perspective 2 Target: Reference Image 2 Final Accuracy: 92.53480%	Perspective 3 Target: Reference Image 4 Final Accuracy: 86.49904%

Figure 6.16: Results using reference images 2, 4, and 5 simultaneously

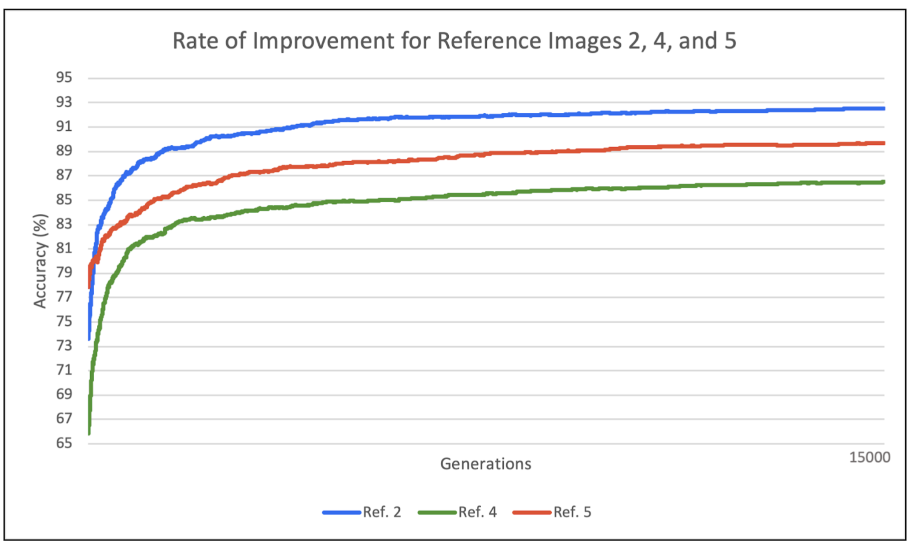


Figure 6.17: Improvement to accuracy over the generations for reference image 2, 4, and 5

Perspective 1 Target: Reference Image 1 Final Accuracy: 90.30935%	Perspective 2 Target: Reference Image 3 Final Accuracy: 91.24382%	Perspective 3 Target: Reference Image 6 Final Accuracy: 83.31394%

Figure 6.18: Results using reference images 1, 3, and 6 simultaneously

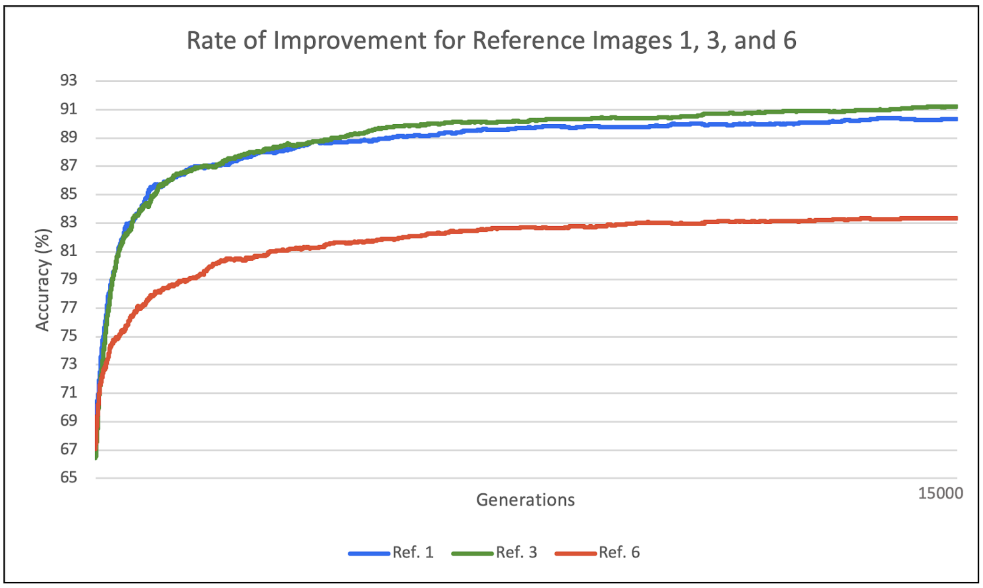


Figure 6.19: Improvement to accuracy over the generations for reference image 1, 3, and 6

Chapter 7

Evaluation

In this study, a collection of digital art pieces were produced. Evaluating how well an algorithm is able to produce digital art is incredibly difficult because art is inherently subjective. The same artwork can be evaluated in many different ways and different people may provide wildly different and even contrasting answers to the same questions. As mentioned before, the accuracy level given to the individual digital art pieces provides a simple numerical metric of how close the digital art is to the reference image but it fails to give a reliable metric on the performance of the digital art from an artistic perspective. For this reason, a survey was conducted with 14 participants in order to obtain a better understanding of people's impression of the digital art produced during this project. The focus of the survey was to have the participant judge each of the digital art pieces in terms of how visually appealing and recognizable they are as these are the hardest elements to judge from a single perspective. The questions and answers of the survey can be seen in the appendix provided with this report.

7.1 Evaluation of the Results

Figures 6.11, 6.13, 6.15, 6.17, and 6.19 show the rate of improvement for each of the reference images during each of the tests. The graphs show a very similar curve to most EAs where the rate of improvement increases dramatically in the first few generations and then gradually slows down as the Organisms converge on an optimal solution. Even though the optimization slows down in the later generations there are still significant improvements being made to the digital art, what seem like small improvements to the accuracy can actually greatly improve the digital art in terms of being visually appealing or recognizable. An example of this could be changing the color of a single Gene, this may improve the accuracy by a very small amount but could result in the formation of a key identifying feature of the reference image (e.g a single dot used to represent an eye on a face). The graphs indicate that perhaps given more generations to run, the digital art would continue to improve. This is especially true for the MOGA using two or three reference images simultaneously. However, due to time constraints the maximum generation was kept at 15,000.

An interesting observation is the trade offs being made between the accuracy of one reference image and another during the optimization. There are times when an Organism in a generation actually performs worse than it did in the previous generation for one reference image, but despite this is considered the best Organism due to a massive improvement in the performance for a different reference image. An example of this can be seen in Figure 6.15 where in the initial generations you can see a point where the accuracy to reference image 3 slightly decreases from one generation to the next while the accuracy to reference image 6 suddenly increases significantly. Nonetheless, generally all the reference images seem to improve at similar rates during the tests.

7.1.1 Using a Single Reference Image

When the algorithm was only given a single reference image the digital art that it produced turned out exceptionally well. Regardless of the Gene types used, the Organisms successfully generated clear illustrations of their target reference images that were easily recognizable. The Organisms using the square and circle Gene types did perform better in terms of creating digital art that kept the intended artistic style of Pointillism. The Organisms using the triangle Gene type created digital art that more closely resembles the artistic style of abstract art, but that is not to say they did not perform well. In fact, on the contrary, in the survey conducted the digital art created for some of the reference images using triangles was actually favoured over the circles and squares in terms of being visually appealing.

7.1.2 Using Multiple Reference Images

As there was no other similar research in the field about generating digital anamorphic sculptures that produced digital art using multiple reference images, it was difficult to predict what the outcome of the MOGA would be. It was expected that the algorithm would have a harder time producing digital art using multiple reference images not only due to the increase of computations required to calculate the score for each new perspective, but also due to the fact that the objectives had a direct impact on each other. Subtle changes that could greatly improve the score given for one objective could also hinder the score for another objective. One of the main concerns in the beginning was whether the Genetic Algorithm would be able to handle the multiple objectives and display the art correctly from each perspective or simply optimize for an incoherent arrangement of Genes that satisfy the scores as best as possible but are incapable of displaying anything.

Surprisingly, the MOGA performed significantly better than initially anticipated. When using two reference images simultaneously. It is clear that the algorithm is able to handle multiple objectives and produce coherent digital art from each perspective.

Of the tests conducted on the MOGA using two reference images, the test that achieved the highest combined accuracy was the test using reference image 1 and reference image 2. Figure 6.10 shows the final digital anamorphic sculpture viewed from each perspective. Despite the fact that the two reference images were visually very different from one another, the correct shapes and colors of the reference images can clearly be seen from each perspective.

Figure 6.12 shows the results of using reference image 4 and reference image 5. These two reference images were chosen to be used together because they seemed to be the most visually similar to one another having many of the same or similar colors. Even though the digital art from this test did not have the highest accuracy among tests using two reference images, they scored some of the highest results in terms of being recognizable in the survey.

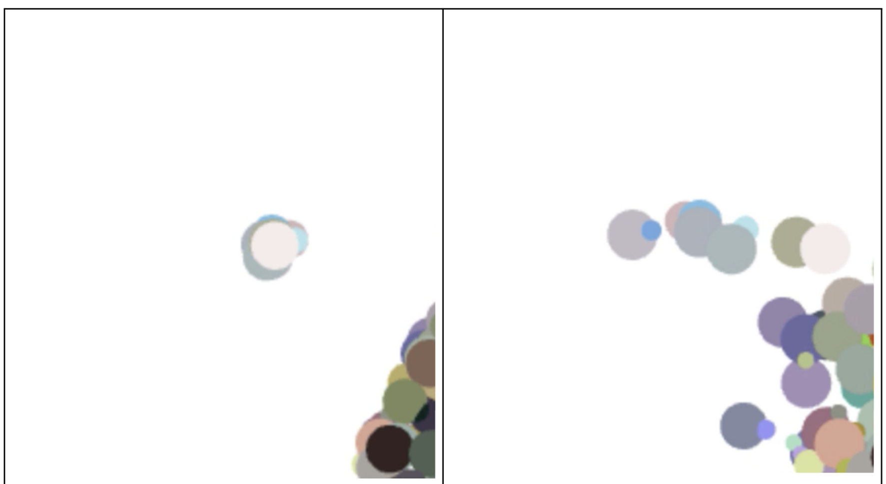
Figure 6.14 shows the results of using reference image 3 and reference image 6. These two images were chosen to be used together in order to stress test the performance of the algorithm as these were the most complex reference images. Even when using these specifically harder reference images, the algorithm was able to achieve a final accuracy of 90.87483% for reference image 3 and 84.67456% for reference image 6, a 3-4% difference from their counterparts created by the algorithm using a single reference image at a time.

The final two tests conducted tested the performance of the algorithm when given 3 reference images. The results of the first test which can be seen in Figure 6.16 used the simpler set of reference images. In this test, it is still clear to identify each of the different reference images even though much of the detail and colors are now cluttered by the increased number of Genes needed. The survey shows that in terms of recognizability, the digital art of reference image 2 in particular even managed to score higher than its counterpart generated by the algorithm only optimising for 2 reference images.

The second and final test used the harder set of reference images and the results of which can be seen in Figure 6.18. This test clearly demonstrates the limitations of this algorithm where much of the detail of the images is lost and even though the general shapes of the reference images are still maintained the Genes are clearly struggling to optimize for the correct colors and positions in order to generate coherent digital art. This is further acknowledged in the survey in which the digital art generated by this test scored poorly in terms of recognizability some answers going as far as stating the digital art had become unrecognizable.

7.2 Notable Behaviour

During the experimentation of the MOGA several interesting behaviours were observed. The MOGA developed several techniques to help improve its performance in generating digital art from multiple perspectives. One of these techniques was the use of “cover-up” Genes. These Genes optimized to become as large and as close to white as possible. They positioned themselves close to one of the perspectives and allowed the algorithm to create a line of other Genes behind it that could be used to improve the digital art for one reference image while not affecting the performance of the other. An example of this technique being used can be seen in Figure 7.1.



This image shows a “cover-up” Gene as seen from one of the perspectives.	This image was taken with the camera slightly shifted to the left in order to show the line of Genes behind the “cover-up” Gene.

Figure 7.1: Screenshot of a section of an Organism containing a "cover-up" Gene

Another noticeable technique used by the MOGA was to find the components of each reference image that had the most similar color to each other and use the same grouping of Genes to optimize for both reference images simultaneously in order to use less Genes overall.

This was achieved by roughly approximating the color of these components for both images creating Genes with colors that were "close enough" to the components of the image they were a part of. An example of this can be seen in Figure [BIRD FROG V] where the Genes that are used to make up the branch the bird is perched on in reference image 1 are also used for the main body of the frog in reference image 2.

7.3 Evaluation of the Work

During the project requirements section of the report a set of requirements were devised to be met in order to ensure that the project could be deemed a success. The GUI met the requirements set out for the UX side of the project, providing users with a clear and easy to use interface to allow them to view and interact with the digital anamorphic sculptures. In terms of the artistic result requirements, the algorithm clearly demonstrated the ability to produce digital art in the artistic style of Pointillism. Answers gathered from the survey indicate that the algorithm was generally successful in the creation of digital art from the digital anamorphic sculptures that were visually appealing and recognizable. The algorithm did end up producing a few inadequate results when using 3 reference images especially when using the harder set of reference images. However, this was expected and provides a clear path for improvements to be made later. The performance requirements were met with varying degrees of success. The algorithm did show that it was able to handle a wide range of different reference images, but had trouble with more complex reference images such as reference images 3 and 6. The program successfully demonstrated its ability to create digital anamorphic sculptures using multiple reference images by testing up to three at a time and the program is able to handle image sizes of any size. However, when using multiple reference images the reference images are required to be the same size as each other.

7.4 Limitations

There are two main areas to focus on when addressing the limitations of the program; handling darker reference images and the score calculations. The program has tremendous difficulty producing digital art from reference images with darker backgrounds. This is due to the fact that significantly more Genes are required in order to cover the default white background of the image. This increase in the number of Genes is so significant it causes the program to run incredibly slow, unable to produce a decent result in any reasonable amount of time. Given a more powerful computer and allowing the algorithm to run for longer generations, I am confident that the algorithm would be able to produce acceptable results. However, it was unreasonable to test the algorithm on these reference images given the hardware available. This limitation could be mitigated by unbounding the size of the Genes allowing them to grow into much larger sizes but as previously mentioned this caused the digital art to lose the intended artistic style of Pointillism.

The score calculation (shown in Figure 4.1) used an euclidean distance metric to determine how similar the pixels in the drawn image were to the pixels in the reference image. However, in the RGB color space calculating the euclidean distance does not always produce the most accurate results [2]. Two colors that may seem practically identical to the human eye might give a greater euclidean distance than two colors that visually seem very different from each other when comparing them in the RGB color space [2]. As the colors were already stored as RGB values, using the RGB color space provided the fastest computation as it did not require the color values to be converted and so it was chosen as a compromise to increase the efficiency of the algorithm.

Chapter 8

Conclusion

In conclusion, the two main objectives of this project were to create digital art from a given reference image in the artistic style of Pointillism and to create digital anamorphic sculptures that depending on the perspective you viewed it, could display the digital art in the same artistic style for one of the multiple given reference images. The results clearly demonstrate the effectiveness of the Genetic Algorithm developed for this project at generating digital art as a solution to an optimization problem and corroborate the results found in similar research papers on the performance of EAs in the production of evolutionary art. The survey conducted provided a better understanding of visual appeal and recognizability of the digital art that was produced by the genetic algorithms. The answers indicated that the performance of the algorithm was largely dependent on the number of reference images used simultaneously. The algorithm was tested on six very different reference images. With regards to the algorithm using a single reference image, the images generated were able to approximate these reference images very closely creating digital art that maintained the intended artistic style of Pointillism and were easily recognizable. While it is clear that more work is needed in order to achieve better results when using multiple reference images, the MOGA successfully handled the optimization of the multiple objectives and managed to generate interesting digital anamorphic sculptures. This paper has taken some of the first steps in exploring the capability of MOGAs in creating digital art from multiple reference images simultaneously and it is hoped that it has sparked the interest of other researchers who may want to continue this research and find new and exciting ways to illustrate the digital art alongside digital anamorphic sculptures.

8.1 Future Work

There are several key aspects of the algorithm developed for this project that could be investigated further in future work. One feature that has interesting potential would be to introduce a local fitness function for the individual Genes in every Organism. Local Gene fitness would open the possibility to test different techniques employed by other EAs such as; increasing the percentage chance of mutation for Genes with lower fitness values, implementing a crossover mechanic that could select the best Genes from both parents, programmatically removing the Genes with the lowest fitness values in order to improve efficiency. Another key feature that could be explored in future work is introducing a method to find better angles for the perspectives to view the digital anamorphic sculptures in order to maximise the number of Genes that could be shared between the reference images. This paper has only explored the use of one specific type of EA. However, there are many different types of EAs that could be adapted in similar ways to create evolutionary art using multiple reference images. Some examples of different types of EAs include; Ant Colony Optimization, Bee Algorithms and Cuckoo Search [24]. Each of these different types of EAs have wildly different approaches and techniques to navigating the solution space and generating optimal solutions. Future work in this area should evaluate the performance of each of these different types of EAs in the production of digital art using multiple reference images simultaneously.

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