# USING AESTHETIC LEARNING MODEL TO CREATE ART

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Abstract: An aesthetic learning model is proposed that applies evolutionary algorithm to generate art. The model is evaluated using an evolutionary art system by human subjects. The advantages of the model is that it helps user to automate the process of image evolution by learning the user's preferences and applying the knowledge to evolve aesthetical images. This paper implements four categories of aesthetic metrics to establish user's criteria. In addition to evolutionary images, external artworks are also included to guide evolutionary process towards more interesting paths. Then we described an evolutionary art system which adopted the aesthetic model in detail. Last, we evaluate the aesthetic learning model in several independent experiments to show the efficiency at predicting user's preferences.



## 1 INTRODUCTION

Evolutionary Art is originated from the work of Dawkins (Dawkins, 1986), his Biomorphs program. Following the earliest ideas of Sims(Sims, 1991) and Latham(Latham and Todd, 1992), which use lisp expressions to specify the color of every pixel, a wide research (see, for example, (Lutton, 2006) (Bentley, 1999) (Machado and Cardoso, 2002)) used Genetic Programming(GP) to evolve aesthetic images. One of the significant challenges faces such systems is to find an appropriate fitness function for guiding the evolutionary process. Nowadays, most systems rely on Interactive Evolutionary Computation (IEC), which the user take the tedious task to make decisions for every generation. However, this could cause serious problems, like premature convergence, user fatigue and several other disadvantages(Takagi, 1998).

Most of the existing systems take a long time to find interesting images. So users usually lost interest in exploring design space further. In order to reduce user fatigue, it is important to prevent stagnation in evolutionary process, keep user's interests high and automate aesthetic judgements. Thus it suffers from at least two major difficulties. First, it is hard to tell exactly what metrics that influence individual's final aesthetic criteria. Second, the searching space is often fixed by a certain style, which stuck the exploring paths in a local optimum. This paper will propose new techniques to solve these two issues.

Considering the above issues, our system is aim at overcoming the drawbacks of existing systems and automating the aesthetic judgements. This goal is achieved by (a)devising several metrics and establishing an aesthetic model for measuring user's aesthetic values; (b)introducing external images to the training samples, which could apply external evaluations and guide the evolutionary process towards more interesting paths.

Three contributions are made by our work. First, four categories of metrics have been established for extracting meaningful aesthetic standards. Second, both internal IEC images and external images collected from internet are included in training the aesthetic model. Third, the model based on a classifier is introduced to automatically distinguish aesthetic images. To further manipulate the evolutionary process easily, intuitive mutation parameters are applied.

Our contributions have been tested with several independent experiments by our system. We monitored how these metrics evolved over iterations, quantitatively influenced the aesthetic model and how the system directed the selection process by using the aesthetic model. We find that the aesthetic model is efficient for most of the users to model their preferences and properly classifying high, medium and low val-

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ued images by learning the interactive run and external images selected by user.

The paper is organized as follows: Section 2 begins with an overview of previous work on automatic fitness assignment and computational aesthetics; in Section 3 we describe our aesthetic model; following with Section 4, which includes a global overview of the system and the experimental results; finally, in Section 5 we draw conclusions and point directions for future research.

## 2 STATE OF ART

Evolutionary Algorithm has been successfully applied in the fields of design (Bentley, 1999), art processing (Bachelier, 2008) and imagery generating (Ventrella, 2008). Most evolutionary art system use IEC technology, which is based on subjective human evaluation (Sims, 1991)(Poli and Cagnoni, 1991)(Lutton, 2006)(Rooke, 2002)(Li et al., 2009). A thorough survey of application and interface research on IEC can be found in (Takagi, 1998). However, the user fatigue is one of the biggest problem in this domain. Therefore, how to automatic the evolution poses significant challenges to this field.

Several systems have been successfully performed automatic evaluation in music composition (Papadoulos and Wiggins, 1999)(Todd and Werner, 1998)(Manaris et al., 2005)(Manaris et al., 2007). While in the field of evolutionary art, it makes the work more difficult due to the lack of explicit theory like in music (for a detailed survey see (Machado et al., 2008)).

Two important issues has been addressed in this paper to formulate an appropriate fitness function for aesthetic purposes. First, what kind of metrics or criteria influence the final aesthetic judgement; Second, the relations among them need to be established to assign aesthetic value.

Taking account of the first issue, the automatic aesthetic judgement falls into the realm of computational aesthetics, which applies computational methods that can make applicable aesthetic decisions in a similar fashion as humans can (Hoenig, 2005). A brief historical review of the origins of the term could be found in (Greenfield, 2005). Birkhoff first formalized the aesthetic metric is the ratio between order and complexity. This metric is then quantified by different measurements on the following work. The work of Bense (Bense, 1969) and Jaume (Rigau et al., 2008) defines the complexity and order from the Shannon's Information Theory(Shannon, 1951). However, it still needs tests to prove its validity, especially the relations between complexity and order.

Later, expression-based evolutionary art system, NEvAr (Machado and Cardoso, 2002) applied an automated fitness assignment, which consider both visually complexity and processing complexity are very important factors. The aesthetic value is estimated through the division of the complexity of visual stimulus and complexity of the percept. The two measurements are implemented by JPEG compression and fractal compression for capturing the self-similarities of the image. This formula is tested by ”Test of Drawing Appreciation”, which is a standardized psychological test to evaluate art aesthetics (Machado and Cardoso, 1998). The result of the test were surprisingly good.

An empirical aesthetic model has been used by Brian et al. for evolutionary image synthesis (Ross et al., 2006). The main metric used in this model is proposed by Ralph (Ralph, 2006), which is based on hundreds of fine art and bell curve distribution has also been found in the color gradients.

The second issue in automatic aesthetic judgement is to incorporate aesthetic criteria and the metrics of image in the evaluation strategy. This is difficult to overcome, because different people have different principles of beauty and appreciations of various metrics.

The most simple way is to merge them together by a weighted sum. The work of (Wannarumon et al., 2008) introduced a hardwired fitness function which combined several measurements that reflect aesthetics of forms and fractals for jewelry design. This measurement is based on mathematical foundations of fractal geometry, chaotic behavior and image processing. But fixed fitness function often introduces bias to the evaluation in evolutionary process.

The first published research which uses machine learning approaches is the work of (Baluja et al., 1994),which relied on ANN to alleviate the burden of users. However, the results turned out to be ”somewhat disappointing” (Baluja et al., 1994). (Ross et al., 2006) use multi-objective fitness testing to evaluate the candidate textures according to multiple criteria. The multi-objective approach to evaluate textures is proposed in (Ross and Zhu, 2004). A Pareto ranking strategy is used to rank the populations, some diversity promoting strategies are then provided to generate a diversity assortment of solutions (Ross et al., 2006). The results show that the techniques are ideally suited to texture synthesis.

Recently, Machado et al. present an IEC with a similarity-based approach in their evolutionary art system (Machado et al., 2008). An Artificial Art Critic (AAC) is introduced to distinguish between external images (e.g., paintings) and the internal images created by evolutionary process. Thus it enables new trends and explorations in stylistic changes.The AAC includes two models: (i) the feature extractor and (ii) Artificial Neural Network (ANN). The evaluator is used to distinguish between the internal and external images (Machado et al., 2008). (Ekart et al., 2011) propose a set of aesthetic measures identified through observation of human selection of images and then use these for automatic evolution of aesthetic images.

# 3 AESTHETIC LEARNING MODEL

Three important issues are addressed in our aesthetic learning model. First, image metrics which we considered very important factors in aesthetic judgements should be calculated in the model. Although different people might disagree on the meaning of beauty, most metrics are primary characteristics of visual systems and user's interest. Second, training populations are specifically chosen for the learning classifier. Outer images are involved to avoid convergency to a specific style. Besides, inner images generated using IEC are also collected for training sets in every iteration. Third, decision tree is used to build the learning model. Applying populations with assigned fitnesses using the model in the continuous generation is one way to reduce the users' fatigue. This is achieved by learning the metrics that extracted from images and applying the model to the following evolutionary process.

## 3.1 Aesthetic Metrics

Inspired by the works of (Rigau et al., 2008), (Schmidhuber, 1997) and (Machado and Cardoso, 1998), we complement the metrics with these theory by considering these established aesthetic measures. This work is a continuation of our previous work that primarily focused on the estimation of image complexity and image order (Li and Hu, 2010). These metrics that we choose fall into four categories: color ingredient, image complexity, image order and metric based on Machado and Cardoso's work(MC metric). These categories are shown in Table 1. Additionally, we divide the original image into five parts to calculate these metrics, because spatial information is able to help analyze different parts of the image.

We apply these metrics to different parts of the image and denote them as $m_i (1 \leq i \leq 14)$, which are described as follows.

Table 1: Aesthetic Metrics Summary

| Category | Description |
|---|---|
| Color Ingredient | Average value and standard deviation of Hue, Saturation and Lightness |
| Image Complexity | Information entropy of HSL, RGB and $Y_{709}$ |
| Image Order | Kolmogorov's complexity based on JPEG and fractal compressor |
| MC metric | Image complexity(IC) and Processing complexity(PC) based on MC |

### 3.1.1 Color Ingredient

Our motivation for the choice of color ingredient is based on HSL color space, which is more intuitive than RGB to describe perceptual color. Hue specifies the base color, the other two specify the saturation and the light of the color, three of which are all important factors addressed in perception. The color channels we used for the color ingredient metric is hue, saturation and lightness. We converted the RGB data of each image to HSL color space, producing three matrices $I_H, I_S, I_L$, each of which the dimension is $M \times N$. Then we proceed by calculating the average value and the standard deviation in each of these three channels.

Although a computer may describe a color using the amounts of red, green and blue, a human probably define it by its attributes of hue, saturation and lightness. Hue is the angle in the color wheel, the first metric is computed as the average value of hue $m_1 = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} I_H(x,y)$. Saturation and lightness are also calculated in the same way using $I_S$ and $I_L$ separately to get the metrics $m_2$ and $m_3$. The averaged saturation indicator represents the purity of the color. While light also turns out to be a very important factor to discriminate between appealing and unappealing images, because sometimes it indicates the sunlight, shadow or darkness.

In addition, the standard deviation of the three channels are computed as metrics $m_4$, $m_5$ and $m_6$. These metrics represents the scale of the color distribution. In the artistic domain, the range of colors in paintings that selected by the artist is the fundamental step to produce a fine art.

### 3.1.2 Image Complexity

Our measurements of image complexity are based on the concepts of information theory. The estimation of the metric has been stated in (Li and Hu, 2010). The relationship between complexity and aesthetics has been widely discussed (Birkhoff, 1933) (Machado and Cardoso, 1998) (Rigau et al., 2008). We use the image complexity measurement from an information-theoretic perspective for this metric. The reason we consider informational aesthetics measurement is in (Rigau et al., 2008).

HSL, RGB and $Y_{709}$ channels are used to calculate the information content of the image. The image complexity for hue channel is computed as follows:

$$m_7 = N \times (-\sum_{x \in X} p_{hue}(x) log p_{hue}(x)). \quad (1)$$

where $p_{hue}$ is the probability distribution in channel hue, which is calculated as follows:

$$p_{hue}(x) = \frac{n_x}{N}(0 \leq x \leq \chi). \quad (2)$$

where $n_x$ is the number of pixels in bin x.The value of $\chi$ is different according to the channel, which represents the bins of the histogram. In our case, $\chi$ for hue, saturation and lightness channel are 360, 100 and 100 respectively. The image complexity is calculated by multiplying each pixel's Shannon entropy in every channel and the number of pixels. $m_8$ and $m_9$ are also computed in the same manner for the information channel of saturation and lightness.

The complexity is also calculated from RGB representation and $Y_{709}$, which is the luminance from linear red, green and blue. In RGB space, we divide it into 512 cubes with eight equal partitions along each axis to reduce the calculation in $256^3$ dimension. The intensity histogram is then reduced to 512 $X_{RGB}$ bins. The $\chi$ for the channel $Y_{709}$ is 256. Probability distributions of the variables $X_{RGB}$ and $X_{Y_{709}}$ are used to calculate the entropy of RGB and $Y_{709}$ channel, which we denote them as the features $m_{10}$ and $m_{11}$.

#### 3.1.3 Image Order

The image order is estimated based on the work of Schmidhuber (Schmidhuber, 1997). (Li and Hu, 2010) have explored the following hypothesis: an image which can be computed by an algorithm in the shortest description is considered the most beautiful in a set of images. The coding algorithm is presented for the description of the human visual system. In our case, we use the real-world fractal compressor to achieve this metric. We choose this image compression method because it is intended to compress in a visible way for human eye. Training images are assigned by three fitness values. Thus the priori distribution of the images, $-logP(i)$, is assigned to 1, 0.5 or 0 which represents high, medium or low value. $logP(C)$, the constant when $C$ is given, is disregarded. According to the definition, the order of the image is calculated as follows:

$$-logP(i \mid C) = \frac{CompressionRatio}{t_e - t_s} - logP(i). \quad (3)$$

$t_e$ and $ts$ are the end-time and start-time of fractal encoding. In order to calculate this evaluation, we first average the RGB pixels into grey ones, then the image is divided into four equal regions. The fractal algorithm encodes each region based on its self-similarity. Thus the metric $m_{12}$ is approximated by the fractal compression.

#### 3.1.4 MC Metric

This metric is based on the aesthetic theory of Machado and Cardoso (Machado and Cardoso, 1998). They stated that the aesthetic value of an artwork is connected to Image Complexity (IC) and Processing Complexity (PC). Although, they developed a formula, the $\frac{IC}{PC}$ ratio, to evaluate the aesthetic value, we consider both complexities are significant metrics for the aesthetic model. Therefore, IC and PC are estimated separately as independent metrics.

In order to compute IC, we compress the image using JPEG compressor. In the compression method, the image is coded with error, we can specify the amount of detail kept and the compression ratio.The IC metric is estimated through the division of the root mean square error(RMSE) by the compression ratio resulting from the JPEG compression, $m_{13} = \frac{RMSE}{CompressionRatio-JPEG}$. Low values of IC indicate substantially compressible and low complexity of the image. While high values of IC indicate not compressible and more complex image.

PC suppose to reflect the compression process of the image. The fractal image compression is somehow closer to the way in which humans process the images. We use fractal image compression for estimating PC. The image varies in perception process as the time passes, so CP is different in every moments. In order to compute PC in different time points $t_0$ and $t_1$, we measure it separately as $PC(t_0)$ and $PC(t_1)$. We argue that PC can be substituted by the following formula:

$$m_{14} = (PC(t_0) \times PC(t_1)) \times (\frac{PC(t_0) - PC(t_1)}{PC(t_1)}). \quad (4)$$

This process yields a total of 14 metrics for the whole image. However, these global metrics could be incorrect. To better capture metrics in different regions of the image, we segment each image into five different partitions: four quadrants and an central square with the same size. Then we applied the same 14 metrics to each of partitions and the global image. Thus a total of 84 features are extracted for each image.

### 3.2 Training Set

In order to build the aesthetic model, a training set of $64 \times 64$ pixel outer and inner images was used.

The process used to obtain these images was as follows. For each generation, one image that the subject choose as the parent of the next generation, as well as other 66 images present on the screen, became the inner candidates for the training set. The subject rank these images into three categories: low, medium and high, which are assigned to values 0.0,0.5 and 1.0 respectively. Although collecting the inner images generated using IEC as the candidates would have been easier than including the real world artworks, it leads to specific stylistic images that belong to the EC-generated class. Therefore, in order to provide the training set with external evaluations, images which the subject selected from paintings, photographs, internet, etc. were required. These outer images are assigned to 1.0 as they were regarded as the interesting images. Through several interactive evolutions, hundreds of images were collected in total.

An image library is built to save different artworks that we collected from internet. During the evolutionary process, the subject can choose any pleasing images from our image library to adjust the model. To train the model, images were scaled to range $60 \times 60$. About 30 paintings were collected from different sources. The paintings are from the artists Edvard Munch, Marc Chagall and Vincent Van Gogh. Paintings from one artist can be chosen to allow a bias towards a particular artist's style, or a set of abstract paintings can be selected to guide the model towards a specific type.

The inner populations are gathered during the evolutionary process. The population size of each iteration is 67. The total number of the inner populations depends on the number of iterations before the evolutionary process stops.

### 3.3 Learning Aesthetic

As we stated, this model is based on a classifier, the input of which is the 84 metrics that we introduced and the fitnesses. The classifier is chosen by the following reasons:(1) we could explore the metrics of image that are shown correlations with user's aesthetic judgement; (2) images could be rendered with fitness assigned by the model in each generation in order to help the user to evaluate populations.

ANN is the mostly used machine learning approach to learn evaluating aesthetic judgments. Although this approach is elegant, the ANN training process is usually time-consuming and not easy to understand. In (Machado et al., 2008), it needs 6 seconds per image to extract features, and ANN training takes hours to train the model. And in the work of Baluja, it becomes a very difficult undertaking to determine what the ANN has 'learned', and an even harder task to translate the knowledge embedded in the ANN into understandable rules (Baluja et al., 1994). These are the two reasons why we use decision trees to build the classifier. By looking at the decision tree, it is easy to see which variables split the data into aesthetic category. This information is very important for us to understand the nature of beauty according to the user's behavior.

Therefore, decision tree is one utility that could help us better understand the influence of different metrics and criterias directly. The structured rules that learned from the model would be applied on the images to assist in making aesthetic decisions. In order to build the classify model, we focus on C4.5 (Quinlan, 1993) decision tree to analyze the users' behavior using WEKA J48 (Witten and Frank, 2000) implementation.

In our paper, we convert our data collected from evolutionary process into a file, which is the input for the algorithm. 84 metrics are the attributes with a set of different real values in several evolutionary run. Then the algorithm of the decision tree recursively divides the dataset into smaller subsets by selecting one of the most informative attribute until it has been labeled as terminal. The model is then constructed by the decision tree, which will be applied in the new evolutionary process. It is used to classify new populations into three categories to help users accomplish the primary evaluation.

## 4 EXPERIMENTS

In this section, we define what kind of evolutionary art system we use for the interactive evolution, how we conduct our experiments to evaluate the aesthetic model, and what subjects participated in our experiments. After that, we present an individual interactive evolution experiment to better understand the aesthetic judgement process, use the automatic model to compare the results, and discuss the effectiveness of the aesthetic model by performing a number of runs for different subjects.

### 4.1 System Description

Our system is comprised of two modules, image generator which uses GP to produce images and aesthetic model. The overall architecture of our system is given in Figure 1. The method we employed in image generator is described in Section 4.1.2. And the aesthetic model is briefly introduced in Section 3.

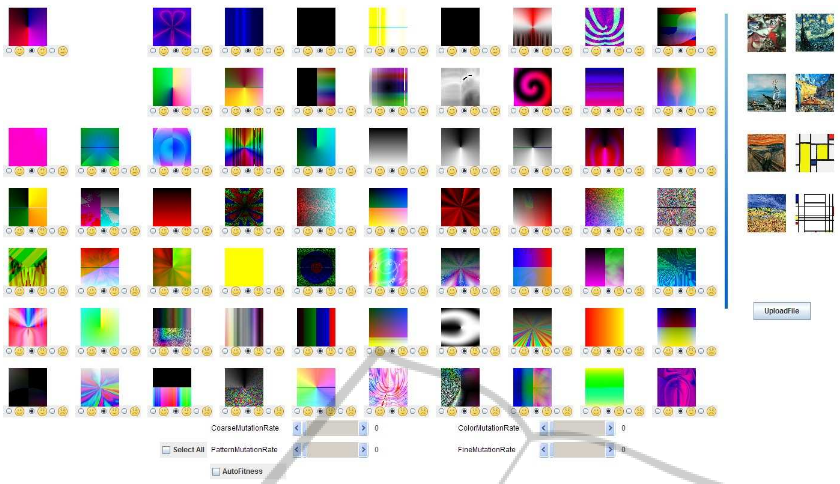


Figure 2: Main window of our system.

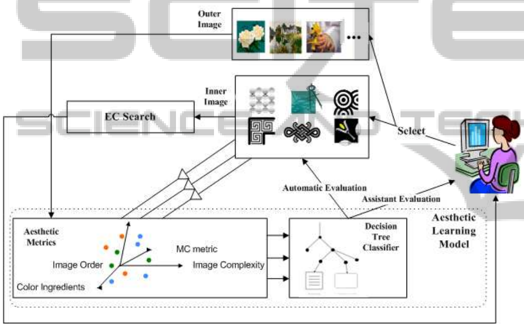


Figure 1: Overall architecture of our system.

#### 4.1.1 Overall Architecture

Our evolutionary art system has four distinctive characteristics. First, we setup four intuitive mutation parameters for user to manipulate the evolutionary process. Second, training samples for the aesthetic model are collected from every generation performed by the user, while images that didn't participate in the evolutionary process are also included. This approach not only enables more stylistic training images introduced in learning process, but also make it more easier to train the model by applying the domestic images. Third, four categories of metrics are extracted from the training samples. Finally, the decision tree is introduced to build the model, and further assist user in assigning fitnesses for the continuous generation.

The main window of the system is shown in Figure 2. Initial populations generated randomly by GP are displayed on the screen. From the displayed set the user can assign fitness by choosing one of the three icons below each image, which represents high, medium or low value. Besides the IEC images, outer images also can be chosen from our painting library during the evolutionary process, which are automatically assigned high fitness values. Four mutation parameters can be set manually to adjust rate of stylistic changing. Evolutionary process stops when the user meets his/her final criteria or he/she loses interest in exploring further populations. *AutoFitness* checkbox is used to collect the data extracted from the previous process, learn the user's aesthetic judgement and build the aesthetic model.

#### 4.1.2 Image Generator

**Genetic Programming**

Like most of the evolutionary art system, the individuals in our system are represented by trees, this shares many similarities with the application developed by Sims. As such, the genotypes are mathematical functions represented by trees, which are constructed by a lexicon of functions and terminals. The functions we use are a set of simple functions, such as transcendental functions, arithmetic operators and logic operations. The terminals are variables x, y, or constants. And then it is normalized into the proper range to specify the color of the pixels.

The symbolic expression is called for every pixel of the image to calculate the color. There are two kinds of root nodes to map the values into color. One is RGB node, which is applied by three channels, red, green and blue to determine the final color. Another one is color map node. The numeric value is called by this node, which is then looked up in a color map to transfer into the real color. In Figure 3 we present some examples of genotype and its corresponding phenotypes.

**Mutation Operators**

Mutation operators are one of the most important genetic operators for the stylistic variations in images.

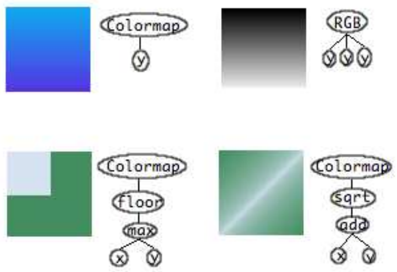


Figure 3: Some examples of genotypes and their corresponding phenotypes.

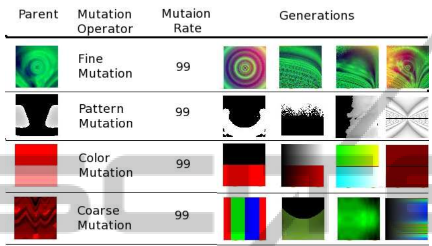


Figure 4: Some examples of generations according to different mutation operators.

Mutation is performed by changing values in a leaf node or functions in an internal node, deleting the subtree at any point or replacing the pruning part with a new random subtree (Li and Hu, 2010). Four kinds of mutation operators are applied in our system, which are coarse mutation rate, color mutation rate, pattern mutation rate and fine mutation rate. They are used to control the rate of changing the subtree, the internal node, the root node and the leaf node. In Figure 4, the parent is the image on the top of the figure, examples of mutation populations generated by different mutation operators with corresponding mutation rates are shown below. Although populations are not precisely transformed by using each mutation operator, they can lead to specific exploration according to users' preference.

#### 4.1.3 Evolutionary and Learning Process

The evolutionary and learning process is briefly described as following steps:

1. A set of initial GP images are displayed on our system.
2. The subject choose his/her favorite images from the image library that we now collected from famous paintings on internet.
3. Fitness values of current populations are assigned by selecting one of the three icons below each image according to his/her preference. The one with high fitness is selected as the parent of next generation. Four mutation parameters are also set manually.
4. Aesthetic metrics are extracted from the current populations and favorite paintings, and then stored in a measure list.
5. The evolutionary process stops when a termination criteria is met. In our case, the number of generations is fixed or the subject choose to train the aesthetic model.
6. The training result is shown on screen, according to which the subject can choose continue training, start over or use the model to continue generating.
7. The model is used to assign fitnesses in the following generations.

Table 2: Parameters of GP for representation.

| Parameter | Setting |
|---|---|
| Population size per generation | 67 |
| Mutation operator | coarse, color, pattern and fine mutation |
| Mutation Rate | manually set every generation, in the range 0-100 |
| Unary function set | sin, cos, tan, abs, floor, ceil, sqr, square, cube, log, exp, negative, spiral, circle |
| Binary function set | +,-,*,/, max, min, pow, average |
| Ternary function set | if, lerp |
| Terminal set X,Y, | scalar and random constants |
| Initial maximum tree depth | 6 |

### 4.2 Experimental Setup

In this section we present some of the experimental results applied with our aesthetic model.

Our intention in implementing this system is not to exclusively reduce errors in learning aesthetic but to decrease the tedious work in IEC process, and try to assist user to interactively evolve images that they find aesthetically pleasing. For this purpose, we are mainly interested in analyzing the metrics relevant to aesthetic judgement, reducing user fatigue and categorizing the populations to help preliminary evaluation. Therefore, we first conducted one single experiment, from the first IEC generation till the last iteration that performed by the model we built. Then we completed 42 runs on our system by 21 different subjects, two experiments by each subject.

In the experiments we use the settings presented in Table 2. 67 images are displayed in every generation, all of which are rendered at 64 by 64 resolution. The functions that we use in GP fall into three categories: unary, binary and ternary functions. The terminals are variable x, y position or constants. The maximum initial tree depth is set to 6.

### 4.3 Analysis of the Model

We conducted one experiment from random populations to the last generation evolved by our aesthetic

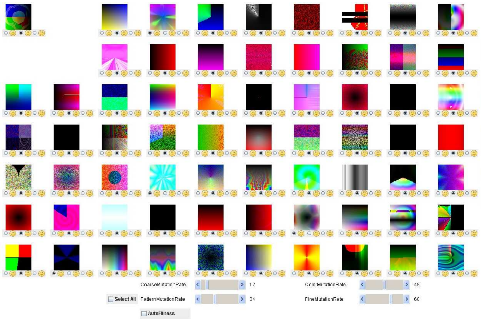

Figure 5: Initial populations of the experiment. The icon below each image indicate the individual's fitness value.

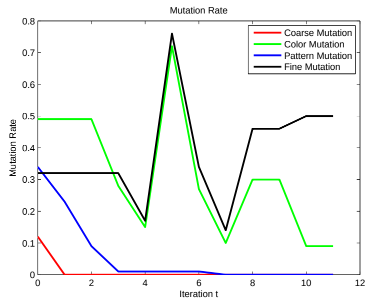


Figure 6: Mutation Rate values along with iterations.

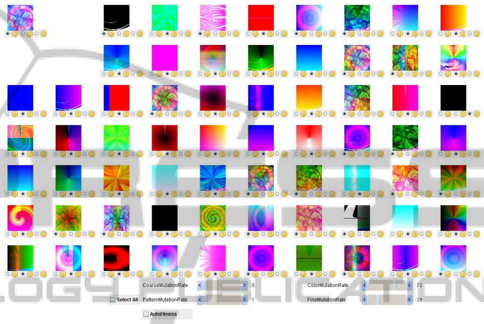

Figure 7: IEC populations from the 5th iteration.

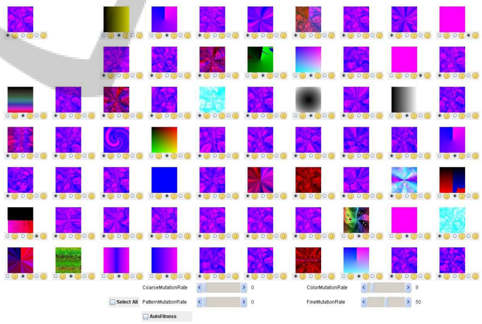

Figure 8: IEC populations from the 10th iteration.

model. In this single experiment, the subject manipulated 10 generations. IEC images generated from iteration to iteration, while eight paintings chosen from our image library remains the same. The number of the outer images still need to be adjusted in the future work to solve the unbalanced classes problem.

### Initial Populations

The initial populations of our system is shown in Figure 5. The population size of the initial random images is 67. These populations were created using random tree depths to avoid monotony of the images. Eight external paintings were also selected by user which we collected from internet. The mutation rates for the next generation were then set separately. The third image from the upper-left corner of the figure was selected as the parent. Parent from every iteration is kept in the next generation, thus genotype with high fitness value occurs more than once in the evolutionary process. In order to remove the repetition in the aesthetic model, we delete the same population that appears in the previous iteration in the training set.

### IEC Results

Considering the main goal of our work, preventing stagnation in evolution and keeping users' interests high is one way to reduce user fatigue. Users usually lost interest in exploring the design space further, because most of the systems produce images that are quite similar to each other or the process leads to blind exploration. Therefore, we applied four mutation operators to better manipulate the exploring paths in search space.

In the experiment the subject performed the experiment as we described before. The mutation rates were set manually, as shown in Figure 6. We present the experimental results attained in the 5th and the last generation in Figure 7 and Figure 8. The results show that from the first iteration till the last, user could easily control the convergence of optimum or maintain sufficient diversity in exploring the design space.

Most of the populations in 5th iteration generates the pattern of a flower. In the following iterations, the user mainly focused on exploring the color and slight variation in shape.

### Training Results

Another method to reduce the evaluation work is to build the aesthetic model to learn the users' preferences. Our aesthetic model first extracted metrics that we stated before from IEC populations and outer images, then the training results is shown on screen (see Figure 9). All the training results, includes roc curves, decision tree and classified rate are displayed. The user decide whether to continue training, start over or apply the model to the following evolutionary runs.

Table 3 shows the accuracy of the correctly classified images with high, medium and low value, which

Table 3: Number of image and correctly classified images.

| | Number of image in training set | Correctly classified Rate |
|---|---|---|
| Low | 30 | 73.33% |
| Medium | 426 | 80.75% |
| High | 345 | 83.19% |

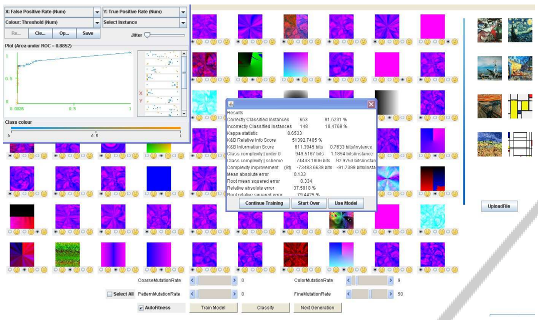

Figure 9: Training results after building aesthetic model.

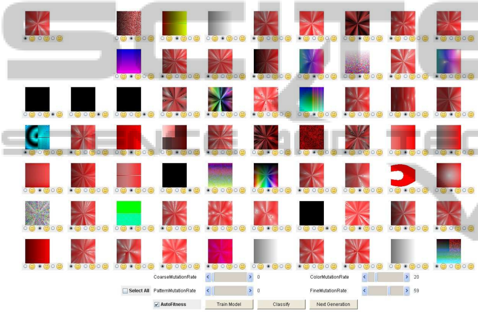

Figure 10: Populations from 30th iteration using the aesthetic model.

we used a 10-fold cross validation. The results show that our system is capable of capturing user's preference from evolutionary process. This is very important for trying to reduce the user's fatigue. The model is applied to help filter out most of the uninteresting populations, thus brings images satisfied users.

The results generated by the model for the following evolutionary runs are shown in Figure10. We find that the aesthetic model is able to distinguish three categories of images. Most of the low value images are correctly classified by the model. And the populations in final iteration share some similarities in stylistic and color with the results generated by IEC.

### 4.4 Subjects Evaluation

We request 21 students in twenties to operate our system, each of which runs twice, with and without aesthetic model. In the first experiment, the subjects performed our system like using most of the evolutionary art system. In the second experiment, the subject used the same populations in the 10th iteration generated in previous experiments (we request subjects perform more than 10 iterations in IEC), then used the training model to generate next 30 iterations and report the fitness categories of the final images for comparison.

Table 4: average test results of 21 subjects on the aesthetic model.

| Mode | Total populations populations | Number of generations | Time consumption | Percentage of high valued images |
|---|---|---|---|---|
| IEC | 884.4 | 13.2 | 10'48" | 43.07% |
| IEC (Aesthetic Model) | 3189.2 | 47.6 | 25'21" | 63.5% |

Table 4 shows the average time consumption, number of populations, number of generations and percentage of high valued images made by human subjects. Clearly, it took 2/3 of the time used by IEC in each iteration using aesthetic model. In other words, more images are generated in certain time with aesthetic model. For IEC with aesthetic model, we also find that the percentage of high valued images is increased although the total number of generation is almost five times more than IEC process. These results show that our aesthetic model is sufficient to predict the user's preference and reduce user's fatigue in the evolutionary process.

## 5 CONCLUSIONS AND FUTURE WORK

This paper introduce an aesthetic model in exploring user's behavior of evaluation in evolutionary art system. The model has incorporated several new ideas in reducing user's fatigue. The metrics we extracted from images are fall into four categories, color ingredient, image complexity, image order and MC metric. Four new features has significantly improved our system for stylistic changing and better exploration. External evaluations of real world paintings or photographs help the model involving outside values of metrics not only limited in IEC space. The four mutation operators can help the system to avid stagnation and blind exploration.

Although more rigorous and more comprehensive evaluation of our model is needed, our preliminary study here does illustrate the efficiency of out system. The future work of this research includes several tasks. First, comparison of different metrics help us to better understand aesthetic criterias in evolutionary process. Second, exploring the relations between the inner IEC evaluations and external evaluations for outer images may also help to analyze the aesthetic model.

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