Evolutionary Computation for Digital Art

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Link to the Current Version

The current version is available at:

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Images and videos are available at:
https://vimeo.com/anetaneumann

Introduction and Motivation

Motivation

- Evolutionary Computation (EC) techniques have been frequently used in the context of computational creativity.
- Various techniques have been used in the context of music and art (see EvoMusArt conference and DETA track at GECCO).

Motivation

- Evolutionary algorithms have been frequently used to optimize complex objective functions.
- This makes them well suitable for generative art where fitness functions are often hard to optimize.
- Furthermore, objective functions are often subjective to the user.

Motivation

- In terms of novel design, evolutionary computation techniques can be used to explore new solutions in terms of different characteristics.
- Evolutionary algorithms are able to adapt to changing environments.
- This makes them well suited to be used in the context of artistic work where the desired characteristics may change over time.

This Tutorial

- Summary of results in the areas of
  - 2D and 3D artifacts
  - Animations
- Overview on our recent work to create unique generative art using evolutionary computation to carry out
  - Image transition and animation
  - Image composition
  - Diversity optimization for images

Outline

- Introduction and Motivation
- Evolving 2D and 3D Artifacts
- Aesthetic Features
- Evolutionary Image Transition
- Evolutionary Painting Using Random Walks
- Quasi-random Image Animation
- Evolutionary Image Composition
- Evolutionary Image Diversity Optimization
- Discrepancy-Based Evolutionary Diversity Optimization for Images
- Indicator-Based Evolutionary Diversity Optimization for Images
- Conclusions

Evolving 2D and 3D Artifacts

Evolving 2D and 3D Artifacts

- *Blind Watchmaker* (Dawkins, 1986) evolved 2D biomorph graphical objects from sets of genetic parameters (combined with Darwinism theory).
- Latham (1985) created *Black Form Synth*. These are hand-drawn "evolutionary trees of complex *forms"* using a set of transformation rules.

Evolving 2D and 3D Artifacts

- In 1991, Sims published his seminal SIGGRAPH paper.
- He introduced the expression-based approach of evolving images.
- He created images, solid textures, and animations using mutations of symbolic lisp expressions.

Evolving 2D and 3D Artifacts

- The mathematical expression is represented as a tree graph structure and used as the genotype.
- The tree graph consists of mathematical functions and operators at the nodes, and constants/variables at the leaves (similar to genetic programming).
- The resulting image is the phenotype.
- To evolve sets of images, it uses crossover and mutation.

Evolving 2D and 3D Artifacts (Sims, 1997)

- *In Galápagos* (Sims, 1997) created an interactive evolution of virtual "organisms" based on Darwinian theory.
- Several computers simulate the growth and characteristic behaviours of a population of abstract organisms.
- The results are displayed on computer screens.

Evolutionary Process (Sims, 1997)

- The offspring are copies and combinations of their parents.
- In addition, their genes are altered by random mutations.
- During evolutionary cycle of reproduction and selection, new organisms are created.

EC System (Sims, 1997)

- The EC system allows users to express their preferences by selecting their preferred display by standing on step sensors in front of those displays.
- The selected display is used for reproduction using mutation/crossover. The other solutions are removed when the new offspring is created.

Evolving 2D and 3D Artifacts (Latham, Todd, 1992)

- Latham, Todd (1992) introduced *Mutator* to generate art and evolve new biomorphic forms.
- The Mutator creates complex branching organic forms through the process of "surreal" evolution.
- At each iteration the artist selects phenotypes that are "breed and grow", and the solutions co-interact.

Other Selected Contributions

- Unemi (1999) developed *SBART*. This is a design support tool to create 2-D images based on user selection.
- Takagi (2001) describes in the survey research on interactive evolutionary computation (IEC) which categorises different application areas.
- Machado and Cardoso (2002) introduced *NEvAr*. *This* is an evolutionary art tool, using genetic programming and automatic fitness assignment.

Other Selective Contributions

- Draves (2005) introduced *Electric Sheep*. *The* system allows a user to approve or disapprove phenotypes.
- Hart (2009) evolved different expression-based images with a focus on colours and forms.
- Kowaliw, Dorin, McCormack (2012) explore a definition of creative novelty for generative art.

Image Morphing (Banzhaf, Graf 1995)

- Banzhaf and Graf (1995) used interactive evolution to help determine parameters for image morphing.
- They combine IEC with the concepts of warping and morphing from computer graphics to evolve images.
- They used recombination of two bitmap images through image interpolation.

Aesthetic Measures

Aesthetic Measures

- Computational aesthetic is a subfield of artificial intelligence dealing with the computational assessment of aesthetic forms of visual art.

- Some general image features that have been used are:
  - Hue
  - Saturation
  - Symmetry
  - Smoothness

Aesthetic Measures

- Examples of aesthetic measurements:

  - Benford's Law
  - Global Contrast Factor
  - Information Theory
  - Reflectional Symmetry
  - Colorfulness

Aesthetic Measures (den Heijer, Eiben 2014)

- den Heijer and Eiben (2014) investigated aesthetic measures for unsupervised evolutionary art.

- Their Art Habitat System uses genetic programming and evolutionary multi-objective optimization.

- They compared aesthetic measurements and gave insights into the correlation of aesthetic scores.

Evolutionary Image Transition

Evolutionary Image Transition

[A. Neumann, B. Alexander, F. Neumann, EvoMUSART 2017, ECJ 2020]

- The main idea compromises of using well-known evolutionary processes and adapting these in an artistic way to create an innovative sequence of images (video).
- The evolutionary image transition starts from given image **S** and evolves it towards a target image **T**
- Our goal is to maximise the fitness function where we count the number of the pixels matching those of the target image.

Evolutionary Image Transition

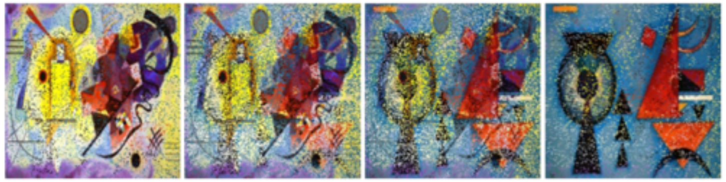
Algorithm 1 Evolutionary algorithm for image transition

- Let S be the starting image and T be the target image.
- Set X:=S.
- Evaluate $f(X,T)$.
- while (not termination condition)
  - Obtain image Y from X by mutation.
  - Evaluate $f(Y,T)$
  - If $f(Y,T) \geq f(X,T)$, set $X := Y$.

Fitness function: $f(X,T) = |\{X_{ij} \in X \mid X_{ij} = T_{ij}\}|$.

Asymmetric Mutation

- We consider a simple evolutionary algorithm that has been well studied in the area of runtime analysis, namely variants of (1+1) EA.
- We adapt an asymmetric mutation operator used in Neumann, Wegener (2007) and Jansen, Sudholt (2010).



Asymmetric Mutation

Algorithm 2 Asymmetric mutation

- Obtain Y from X by flipping each pixel X_{ij} of X independently of the others with probability $c_s/(2|X|_S)$ if $X_{ij} = S_{ij}$, and flip X_{ij} with probability $c_t/(2|X|_T)$ if $X_{ij} = T_{ij}$, where $c_s \geq 1$ and $c_t \geq 1$ are constants, we consider $m = n$.

- for our experiments we set c_s =100 and c_t=50.

Example Images

Starting image S (Yellow-Red-Blue, 1925 by Wassily Kandinsky) and target image T (Soft Hard, 1027 by Wassily Kandinsky)

Video: Asymmetric Mutation

Uniform Random Walk

- A *Uniform Random Walk* - the classical random walk chooses an element $X_{kl} \in N(X_{ij})$ uniformly at random.
- We define the neighbourhood $N(X_{ij})$ of X_{ij} as

$$N(X_{ij}) = \{X_{(i-1)j}, X_{(i+1)j}, X_{i(j-1)} X_{i(j+1)}\}$$

Uniform Random Walk

Algorithm 3 Uniform Random Walk

- Choose the starting pixel $X_{ij} \in X$ uniformly at random.
- Set $X_{ij} := T_{ij}$.
- while (not termination condition)
  - Choose $X_{kl} \in N(X_{ij})$ uniformly at random.
  - Set $i := k$, $j := l$ and $X_{ij} := T_{ij}$.
- Return X.

Video – Uniform Random Walk

Biased Random Walk

- A *Biased Random Walk* - the probability of choosing the element X_{kl} is dependent on the difference in RGB-values for T_{ij} and T_{kl}.

Biased Random Walk

Algorithm 4 Biased Random Walk

- Choose the starting pixel $X_{ij} \in X$ uniformly at random.
- Set $X_{ij} := T_{ij}$.
- while (not termination condition)
  - Choose $X_{kl} \in N(X_{ij})$ according to probabilities $p(X_{kl})$.
  - Set $i := k$, $j := l$ and $X_{ij} := T_{ij}$.
- Return X.

Biased Random Walk

We denote by T^r_{ij}, 1 ≤ r ≤ 3, the rth RGB value of T_{ij} and define

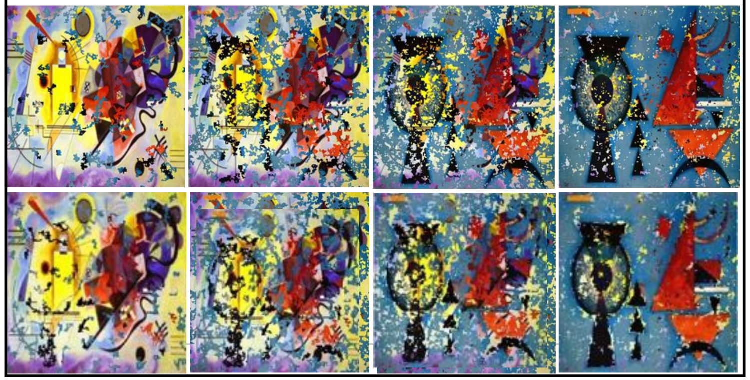
$$\gamma(X_{kl}) = \max\left\{\sum_{r=1}^{3} |T^r_{kl} - T^r_{ij}|, 1\right\}$$

$$p(X_{kl}) = \frac{(1/\gamma(X_{kl}))}{\sum_{X_{st}\in N(X_{ij})}(1/\gamma(X_{st}))}.$$

Mutation Based on Random Walks

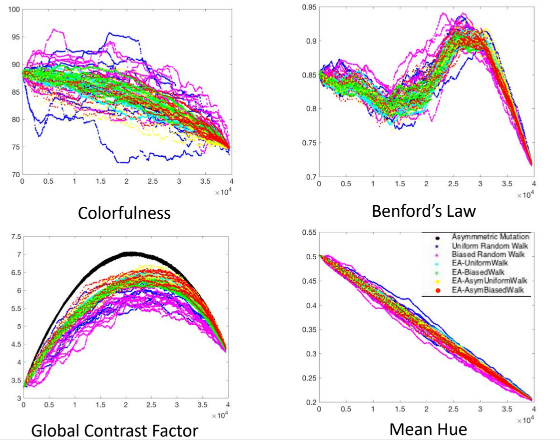
- We use the random walk algorithms as part of our mutation operators.
- Each mutation picks a random pixel and runs the (biased) random walk for t_{max} steps.
- For our experiments we use 200x200 images and set t_{max}=100.

Random Walk Mutation and Biased Random Walk Mutation



Videos - Biased Random Walk Evolutionary Algorithm

Feature Values During Transition:



Evolutionary Image Transition and Painting Using Random Walks

Evolutionary Image Painting

[A. Neumann, B. Alexander, F. Neumann, ECJ 2020]

- We now introduce evolutionary image painting based on biased random walks.
- The key idea is to make use of the biased random walk and use its behaviour of favouring similar colours.
- The mutation operator uses the biased random walk for a given starting pixel and paints each visited pixel with the colour of the starting pixel.

Evolutionary Image Painting

Algorithm 5 Evolutionary image painting

- Let S be the starting image and T be the target image.
- Set $X := S$.
- while (not termination condition)
  - $Y := X$.
  - For each $Y_{ij} \in Y$ with $(Y_{ij} == S_{ij})$.
    - Do Y:=PaintMutation$(Y_{ij}, Y, S, T, \alpha, t_{\max})$ with probability $\min\{c_s/(2|X|_S), 1\}$.
  - Set $X := Y$.

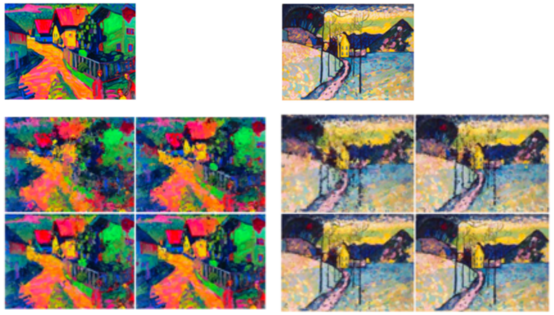
Fitness function: $f(X,T) = |\{X_{ij} \in X \mid X_{ij} = T_{ij}\}|$.

Painting Mutation Operator

Algorithm 6 PaintMutation$(X_{ij}, X, S, T, \alpha, t_{\max})$

- Set $C := T_{ij}$.
- Set $X_{ij} := C$.
- $c := 0$.
- while $(c \leq t_{\max})$
  - $c := c + 1$
  - Choose $X_{kl} \in N(X_{ij})$ according to probabilities $p(X_{kl}, \alpha)$.
  - Set $i := k, j := l$.
  - If $(X_{ij} == S_{ij})$ then $X_{ij} := C$.
- Return X.

Evolutionary Image Painting



Evolutionary Image Painting with t_{max} = 500 and α = 0.25, 0.5, 0.75, 1.0.

Evolutionary Image Painting

Evolutionary Image Painting with t_{max} = 500 and α = 0.25, 0.5, 0.75, 1 (from left to right).

Quasi-random Transition and Animation

Quasi-random Walks

[A. Neumann, F. Neumann, Friedrich, AJIIPS Journal 2019]

- So far: Random walks as main operators for mutation and transition process
- Quasi-random walks give a (deterministic) alternative which is easy to control by a user.

Quasi-random Transition and Animation

General setting:

- There are k agents each of them painting their own image I^k through a quasi random walk. Quasi-random walk is determined by the sequence that the agent uses.
- Process starts with a common image X.
- All agents paint on this image overriding X and previous painting of other agents.
- This leads to complex animation processes.
- Image transition is a special case where all agents paint the same image I.

Agent Moves

Move of an agent:

- Each pixel has a sequence of directions out of from
  {left, right, up, down}.
- At each iteration, the agent moves from its current pixel p to the neighbor pixel p' determined by the current position in the sequence at p.
- It paints pixel p' with the current pixel in its sequence and increases the position counter at p by 1 (modulo sequence length).

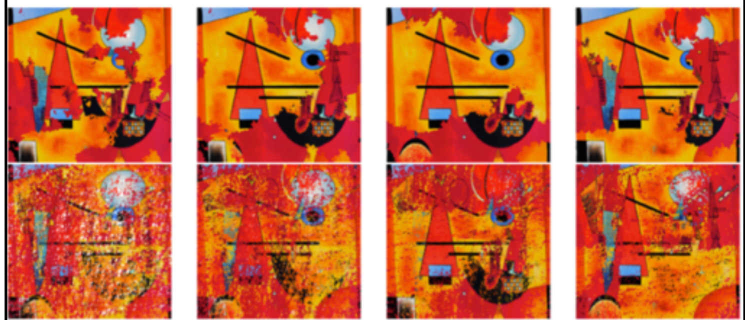
Algorithm

Algorithm 1 QUASI-RANDOM ANIMATION

Require: Start image Y of size $m \times n$. For each agent k, $1 \leq k \leq r$, an image I^k of size $m \times n$, sequence S^k and position counters $c^k(i,j) \in \{0, \ldots, |S^k|\}$, $1 \leq i \leq m, 1 \leq j \leq n$.

$X \leftarrow Y$
for each agent k, $1 \leq k \leq r$ **do**
    choose $P^k \in m \times n$ and set $X(P^k) := I^k(P^k)$.
end for
$t \leftarrow 1$
while $(t \leq t_{\max})$ **do**
    for each agent k, $1 \leq k \leq r$ **do**
        Choose $\hat{P}^k \in N(P^k)$ according to $S_k(c(P^k))$.
        $X(\hat{P}^k) \leftarrow I^k(\hat{P}^k)$
        $c^k(P^k) \leftarrow (c^k(P^k) + 1) \mod |S^k|$.
        $P^k \leftarrow \hat{P}^k$.
    end for
    $t \leftarrow t + 1$
end while

2 Agents Symmetric and Asymmetric Sequences



Example Video: 4 Agents Symmetric Sequences

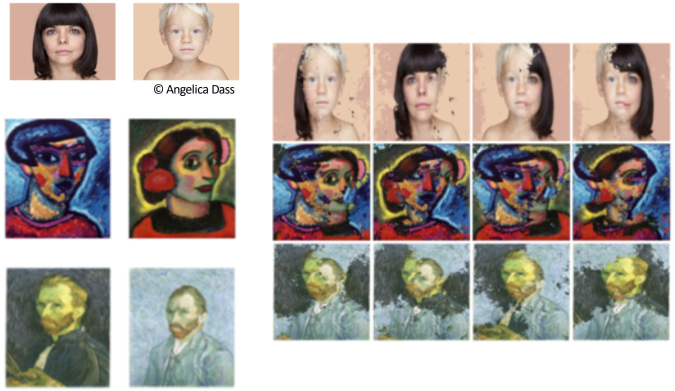
Example Video: 4 Agents Asymmetric Sequences

Evolutionary Image Composition

Key Idea

- Create a composition of two images using a region covariance descriptor.
- Incorporate region covariance descriptors into fitness function.
- Use Evolutionary algorithms to optimize the fitness such that a composition of the given two images based on the considered features is obtained.

Image Composition



Evolutionary Image Composition Using Feature Covariance Matrices

[A. Neumann, Szpak, Chojnacki, F. Neumann , GECCO 2017]

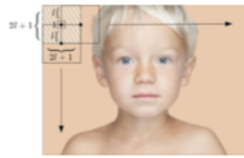
- Evolutionary algorithms that create new images based on a fitness function that incorporates feature covariance matrices associated with different parts of the images.
- Population-based evolutionary algorithm with mutation and crossover operators based on random walks.

Algorithm 1 ($\mu + 1$) GA for evolutionary image composition

```
Require: S and T are images
Initialise population 𝒫 = {P_1, ..., P_μ}
while not termination condition do
    Select an individual P_i ∈ 𝒫 uniformly at random
    if rand() < p_c then                                  ▷ Crossover
        Select P_j ∈ 𝒫 \ P_i uniformly at random
        if rand() < 0.5 then                     ▷ See Section 4.2 for t_cr
            Y ← RandomWalkMutation(X,Z,t_cr)
        else
            Y ← RectangularCrossover(P_i,P_j)
        P_i ← Selection(P_i,Y)
    else                                                   ▷ Mutation
        if rand() < 0.5 then
            Y ← RandomWalkMutation(P_i,S,t_max)
        else
            Y ← RandomWalkMutation(P_i,T,t_max)
        P_i ← Selection(P_i,Y)
        Adapt t_max                                    ▷ See Section 4.1.
return 𝒫                        ▷ Result is a population of evolved images.
```

#3

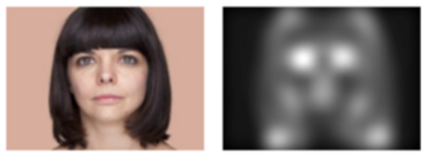
square region of interest



$$\mathcal{G} = \left\{ (c,d) \,\middle|\, \begin{array}{l} c = (l+1) + pl,\ p = 0,1,\ldots,\left\lfloor \frac{m-l}{l} \right\rfloor - 1 \\ d = (l+1) + ql,\ q = 0,1,\ldots,\left\lfloor \frac{n-l}{l} \right\rfloor - 1 \end{array} \right\}$$

#4

saliency mask



#5
set of features

Set 1: $\left[i, j, r, g, b, \sqrt{(\frac{\partial I}{\partial i})^2 + (\frac{\partial I}{\partial j})^2}, \tan^{-1}\left(|\frac{\partial I}{\partial i}|/|\frac{\partial I}{\partial j}|\right)\right]^{\mathsf{T}}$;

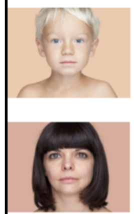
Set 2: $[i, j, h, s, v]^{\mathsf{T}}$;

Set 3: $\left[h, s, v, \sqrt{(\frac{\partial I}{\partial i})^2 + (\frac{\partial I}{\partial j})^2}, \tan^{-1}\left(|\frac{\partial I}{\partial i}|/|\frac{\partial I}{\partial j}|\right)\right]^{\mathsf{T}}$.

#6
covariance-based fitness function

$$f(X, S, T) = \sum_{(c,d)\in \mathcal{G}} \left(w^{S}_{(c,d)} \mathrm{dist}\left(\Lambda^{X}_{\mathcal{R}_{(c,d)}}, \Lambda^{S}_{\mathcal{R}_{(c,d)}}\right) + w^{T}_{(c,d)} \mathrm{dist}\left(\Lambda^{X}_{\mathcal{R}_{(c,d)}}, \Lambda^{T}_{\mathcal{R}_{(c,d)}}\right)\right),$$

Impact of Different Features



© Angelica Dass

Image composition with different features. Rows 1, 2 and 3 correspond to Feature Sets 1, 2 and 3, respectively.

Impact of Different Weightings

Rows 1, 2 and 3 correspond to $w^{S}_{(c,d)}$ set to 0.25, 0.5 and 0.75 and $w^{T}_{(c,d)}$ set to 0.75, 0.5 and 0.25, respectively. In the last row the weights were set using an image saliency algorithm. The saliency algorithm strikes a consistent balance between notable regions in both images.

Impact of Distance Metrics

Rows 1, 2 and 3 correspond to distance metrics $dist_E$, $dist_A$ and $dist_L$, respectively.

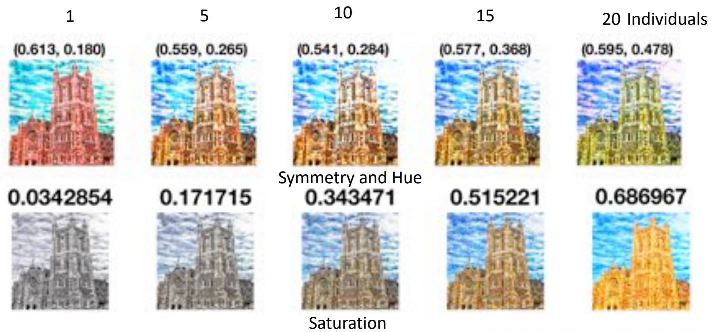
Variants of Image Composition

Image composition with Feature Set 1, saliency-based weighting and a Log-Euclidean distance measure.

Evolutionary Diversity Optimisation
for Images

Key Idea

- Produce diverse image sets using evolutionary computation methods.
- Use the $(\mu + \lambda)-EA_D$ for evolving image instances
- Select the individuals based on their contribution to diversity of the image.



Evolution of Artistic Image Variants Through Feature Based Diversity Optimisation

[Alexander, Kortman, A. Neumann, GECCO 2018]

- We use $(\mu + \lambda)\text{–}EA_D$ to evolve diverse image instances.
- Knowledge on how we can combine different image features to produce interesting image effects.
- Study how different combinations of image features correlate when images are evolved to maximise diversity.

Algorithm 1 The $(\mu + \lambda) - EA_D$ algorithm   μ = 20 and λ = 10

```
input: an image S.
output: a population P = {I_1, ..., I_μ} of image variants.
{Initialise with μ mutated copies of source image}
P = {mutate(S), ..., mutate(S)}
repeat
  randomly select C ⊆ P where |C| = λ
  for I ∈ C do
    produce I' = mutate(I)
    if valid(I') then
      add I' to P
    end if
  end for
  while |P| > μ do
    remove an individual I = arg min_{J∈P} d(J, P)
  end while
until Termination condition reached
```

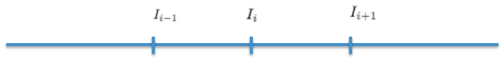
#1
starting image

#2
pixel-based mutation

#3
image validity check

Image has mean squared error to starting image less than 10

#4
feature diversity measure



$$f(I_1) \leq f(I_2) \leq \ldots \leq f(I_k),\ f(I_i) \neq f(I_1) \neq f(I_k)$$

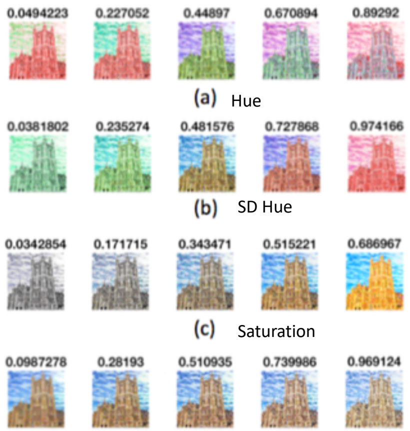
$$d_{f_i}(I_i, P) = (f(I_i) - f(I_{i-1})) \times (f(I_{i+1}) - f(I_i))$$

$$d'(I, P) = \sum_{i=1}^{k} (w_i \times d_{f_i}(I, P))$$

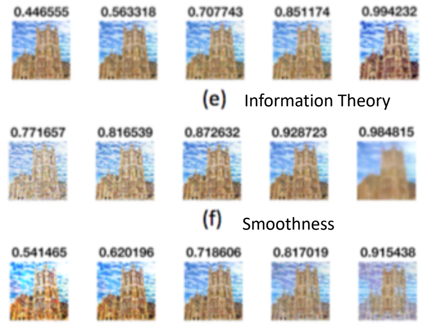
[Gao, Nallaperuma, F. Neumann, PPSN 2016,arxiv2016]

Single Dimensional Feature Results

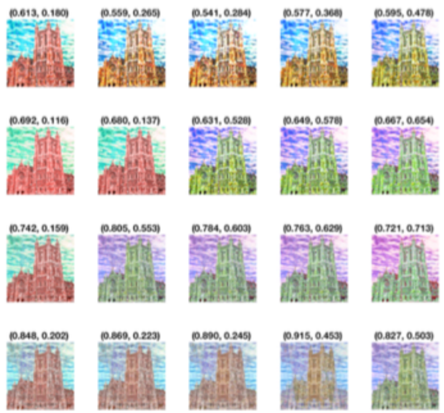
#5 features



Single Dimensional Feature Results



Two-Dimensional Feature Experiments



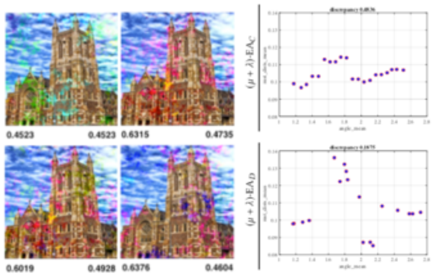
a) Symmetry and Hue 20 Individuals

Discrepancy-Based Evolutionary Diversity Optimization for Images

Our Goal and Key Idea

- Design new approach of discrepancy-based evolutionary diversity optimization.
- Construct sets of solutions for evolved images and instances of Travel Salesman Problem.
- Compare discrepancy-based $(\mu + \lambda)$-EA_D with respect to different features to $(\mu + \lambda)$-EA_T and $(\mu + \lambda)$-EA_C .

A contribution to discrepancy-based evolutionary diversity optimization.



Discrepancy-Based Evolutionary Diversity Optimization

[A. Neumann, Gao, C. Doerr, F. Neumann, Wagner, GECCO 2018]

- New approach for discrepancy-based evolutionary diversity optimization
- Investigate the use of the star discrepancy measure for diversity optimization for images and TSP instances
- Introduce an adaptive random walk mutation operator based on random walks
- Compared the previously approach for images and TSP instances [Alexander, Kortman, A. Neumann, GECCO 2017]

Discrepancy-Based Evolutionary Diversity Optimization for Images

#1

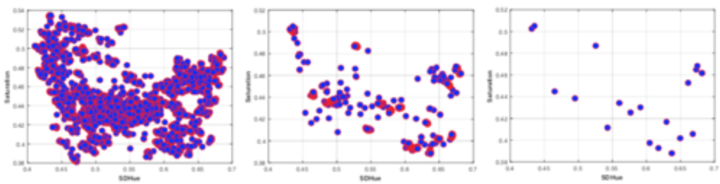
Start Image

#2

Features

#2

Features

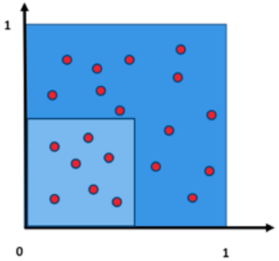


3 Discrepancy

Given a set of points X :={s¹,..., sⁿ}
with S = [0, 1]ᵈ · s¹,..., sⁿ ∈ S

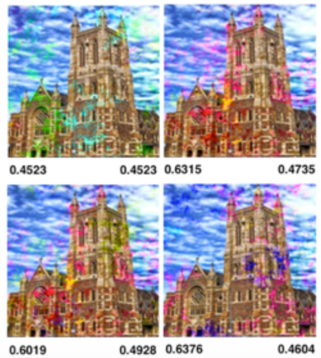
$[a, b] := [a_1, b_1] \times \ldots \times [a_d, b_d]$

$\mathrm{Vol}([a, b]) - |X \cap [a, b]|/n$



$D(X, \mathcal{B}) := \sup\{\mathrm{Vol}([a, b]) - |X \cap [a, b]|/n \mid a \leq b \in [0, 1]^d\}$

Discrepancy-Based Evolutionary Diversity Optimization for Images



#4

Experimental settings

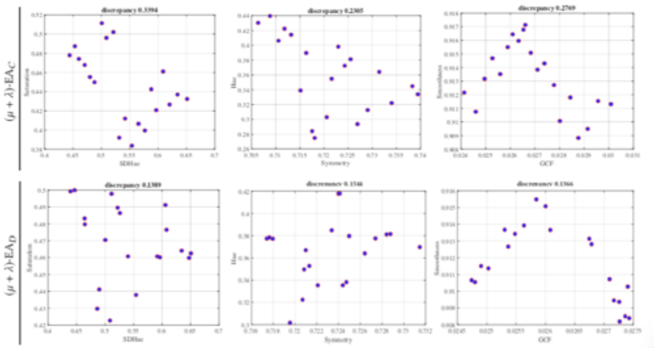
#5

Results

Discrepancy-Based Evolutionary Diversity Optimization for Images

#5

Results



Discrepancy-Based Evolutionary Diversity Optimization for Images

#5

Results

	$(\mu+\lambda)$-EA_C(1)				$(\mu+\lambda)$-EA_D (2)				$(\mu+\lambda)$-EA_T(3)			
	min	mean	std	stat	min	mean	std	stat	min	mean	std	stat
(f1, f2)	0.2014	0.3234	0.0595	$2^{(-)},3^{(-)}$	0.1272	0.2038	0.1157	$1^{(+)}$	0.1119	0.1530	0.0269	$1^{(+)}$
(f3, f4)	0.1964	0.2945	0.0497	$2^{(-)},3^{(-)}$	0.1574	0.2280	0.0592	$1^{(+)},3^{(-)}$	0.1051	0.1417	0.0179	$1^{(+)},2^{(+)}$
(f5, f6)	0.1997	0.2769	0.0344	$2^{(-)},3^{(-)}$	0.1363	0.2025	0.0538	$1^{(+)}$	0.1457	0.1800	0.0234	$1^{(+)}$
(f1, f2, f3)	0.3389	0.4327	0.0613	$2^{(-)},3^{(-)}$	0.1513	0.3335	0.1062	$1^{(+)}$	0.2253	0.2814	0.0422	$1^{(+)}$
(f1, f4, f3)	0.2754	0.3395	0.0483	$2^{(-)},3^{(-)}$	0.2100	0.3118	0.1309	$1^{(+)}$	0.2224	0.2600	0.0123	$1^{(+)}$
(f5, f4, f2)	0.4775	0.6488	0.0841	$2^{(-)},3^{(-)}$	0.2021	0.3007	0.1467	$1^{(+)}$	0.1983	0.2229	0.0125	$1^{(+)}$

Indicator-Based Evolutionary Diversity Optimization for Images

Evolutionary Diversity Optimization Using Multi-Objective Indicators

[A. Neumann, Gao, Wagner, F. Neumann, GECCO 2019, nominated for the best paper in Track Genetic Algorithms]

- Let I be a search point
  - f: X → R^d a function that assigns to each search point I an objective vector
  - q: X → R be a function measures constraint violations
- An indicator I: 2^X → R measures the quality of a given set of search points.

Indicator-Based Diversity Optimisation

- Let I be a search point
  - f: X → R^d a function that assigns to each search point a feature vector
  - q: X → R be a function assigning a quality score to each I ∈ X
  - Require q(I) ≥ α for all "good" solutions (constraint)
- Define D : 2^X → R which measures the diversity of a given set of search points.

Goal:

Compute set P = {I_1, ..., I_μ} of μ solutions maximizing (minimizing) D among all sets of μ solutions under the condition that q(I) ≥ α holds for all I ∈ P, where α is a given quality threshold.

Multi-Objective Indicators

Popular indicators in multi-objective optimization:

- Hypervolume (HYP)

$$HYP(S,r) = VOL\left(\cup_{(s_1,\ldots,s_d)\in S} [r_1,s_1] \times \cdots [r_d,s_d]\right)$$

- Inverted generational distance (IGD) (with respect to reference set R) $IGD(R,S) = \frac{1}{|R|}\sum_{r\in R}\min_{s\in S} d(r,s),$

- Additive epsilon approximation (EPS) (with respect to reference set R)

$$\alpha(R,S) := \max_{r\in R}\min_{s\in S}\max_{1\le i\le d}(s_i - r_i).$$

How to use Multi-Objective Indicators

- Diversity optimisation aims to compute a diverse set of solutions for a given single-objective problem
- Multi-objective indicators guide the search towards a diverse set of Pareto optimal solutions.

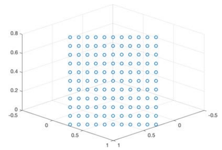
Use of multi-objective indicators:

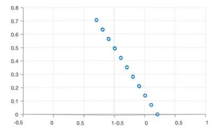
- Transform feature vectors of search points to make them incomparable.
- Apply multi-objective indicators after transformation has occurred.

Transformation:

For 2 features (transform into 3D) as follows:

- Place the unit square with its original x/y-coordinates in the three- dimensional space using z = 0.
- We rotate it around the x and y axis by 45 degrees each time.
- Translate it such that the center point of the transformed unit square is at (sqrt(2)/4)



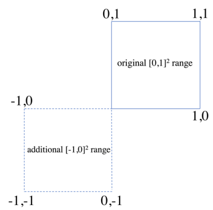


Transformations

For d features:

- Double the number of dimensions to make vectors incomparable.
- For feature value p_i, use p_i and $-p_i$
- Instead of $p = (p_1, p_2, \ldots, p_d)$ work with

  $p' = (p_1, p_2, \ldots, p_d, -p_1, -p_2, \ldots, -p_d)$

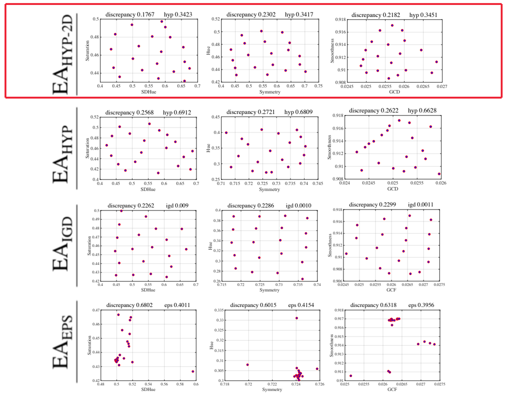


Algorithm

Algorithm 1: $(\mu + \lambda)$-EA_D

1. Initialize the population P with μ instances of quality at least α.
2. Let $C \subsetneq P$ where $|C| = \lambda$.
3. For each $I \in C$, produce an offspring I' of I by mutation. If $q(I') \geqslant \alpha$, add I' to P.
4. While $|P| > \mu$, remove an individual with the smallest loss to the diversity indicator D.
5. Repeat step 2 to 4 until termination criterion is reached.

Multi-Objective Indicators (Images)



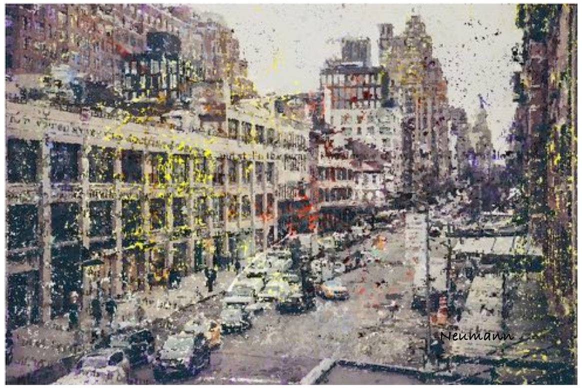
Feature vectors for final population of $EA_{HYP\text{-}2D}$ (top), EA_{HYP}, EA_{IGD} and EA_{EPS} (bottom) for images based on pair of features from left to right: (f1, f2), (f3, f4), (f5, f6).

Results Images

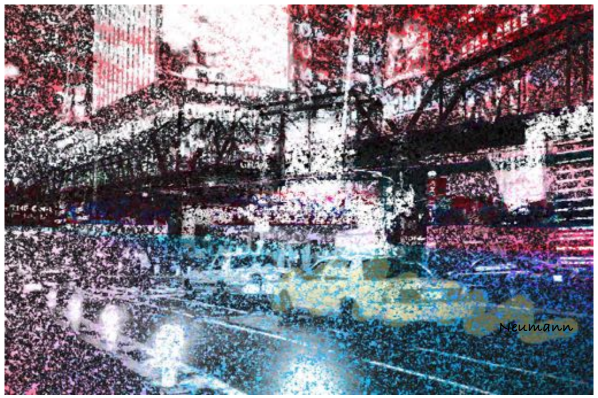
		$EA_{HYP\text{-}2D}$ (1)			EA_{HYP} (2)			EA_{IGD} (3)			EA_{EPS} (4)			EA_{DIS} (5)		
		mean	st	stat	mean	st	stat	mean	st	stat	mean	st	stat	mean	st	stat
HYP-2D	f_1,f_2	0.347	0.004	$4^{(+)},5^{(+)}$	0.382	0.007	$3^{(+)},4^{(+)},5^{(+)}$	0.335	0.003	$2^{(-)},5^{(+)}$	0.198	0.019	$1^{(-)},2^{(-)}$	0.112	0.030	$1^{(-)},2^{(-)},3^{(-)}$
	f_3,f_4	0.344	0.004	$2^{(+)},4^{(+)},5^{(+)}$	0.268	0.014	$1^{(-)},3^{(-)},4^{(+)},5^{(+)}$	0.339	0.004	$2^{(+)},4^{(+)},5^{(+)}$	0.221	0.015	$1^{(-)},2^{(-)},3^{(-)}$	0.105	0.025	$1^{(-)},2^{(-)},3^{(-)}$
	f_5,f_6	0.350	0.007	$2^{(+)},3^{(+)},4^{(+)},5^{(+)}$	0.342	0.004	$1^{(-)},4^{(+)},5^{(+)}$	0.332	0.004	$1^{(-)},4^{(+)},5^{(+)}$	0.220	0.045	$1^{(-)},2^{(-)},3^{(-)}$	0.134	0.016	$1^{(-)},2^{(-)},3^{(-)}$
HYP	f_1,f_2	0.525	0.012	$3^{(+)},4^{(+)},5^{(+)}$	0.693	0.013	$3^{(+)},4^{(+)},5^{(+)}$	0.374	0.006	$1^{(-)},2^{(-)},4^{(+)}$	0.344	0.003	$1^{(-)},2^{(-)},3^{(-)}$	0.363	0.014	$1^{(-)},2^{(-)}$
	f_3,f_4	0.500	0.007	$3^{(+)},4^{(+)},5^{(+)}$	0.681	0.010	$3^{(+)},4^{(+)},5^{(+)}$	0.268	0.072	$1^{(-)},2^{(-)},4^{(+)},5^{(+)}$	0.280	0.010	$1^{(-)},2^{(-)},3^{(-)}$	0.267	0.014	$1^{(-)},2^{(-)},3^{(-)}$
	f_5,f_6	0.518	0.012	$2^{(-)},4^{(+)},5^{(+)}$	0.663	0.010	$1^{(+)},3^{(+)},4^{(+)},5^{(+)}$	0.335	0.004	$2^{(-)},4^{(+)}$	0.317	0.006	$1^{(-)},2^{(-)},3^{(-)}$	0.327	0.008	$1^{(-)},2^{(-)}$
IGD	f_1,f_2	0.001	0.335	$2^{(+)},4^{(+)},5^{(+)}$	0.003	0.000	$1^{(-)},3^{(-)}$	0.001	0.000	$2^{(+)},4^{(+)},5^{(+)}$	0.003	0.000	$1^{(-)},3^{(-)},5^{(+)}$	0.005	0.001	$1^{(-)},3^{(-)},4^{(-)}$
	f_3,f_4	0.001	0.339	$2^{(+)},4^{(+)},5^{(+)}$	0.004	0.000	$1^{(-)},3^{(-)},5^{(+)}$	0.001	0.000	$2^{(+)},4^{(+)},5^{(+)}$	0.003	0.000	$1^{(-)},3^{(-)},5^{(+)}$	0.005	0.001	$1^{(-)},2^{(-)},3^{(-)},4^{(-)}$
	f_5,f_6	0.002	0.332	$2^{(+)},5^{(+)}$	0.007	0.000	$1^{(-)},3^{(-)},4^{(-)},5^{(-)}$	0.001	0.000	$2^{(+)},4^{(+)},5^{(+)}$	0.003	0.001	$2^{(+)},3^{(-)}$	0.004	0.001	$1^{(-)},2^{(+)},3^{(-)}$
EPS	f_1,f_2	0.190	0.198	$2^{(+)},4^{(+)},5^{(+)}$	0.498	0.011	$1^{(-)}, 3^{(-)}$	0.194	0.032	$2^{(+)},4^{(+)},5^{(+)}$	0.402	0.039	$1^{(-)},3^{(-)},5^{(+)}$	0.600	0.106	$1^{(-)},3^{(-)},4^{(-)}$
	f_3,f_4	0.198	0.221	$2^{(+)},4^{(+)},5^{(+)}$	0.569	0.016	$1^{(-)},3^{(-)}$	0.208	0.035	$2^{(+)},4^{(+)},5^{(+)}$	0.418	0.036	$1^{(-)},3^{(-)},5^{(+)}$	0.615	0.069	$1^{(-)},3^{(-)},4^{(-)}$
	f_5,f_6	0.125	0.220	$2^{(+)},4^{(+)},5^{(+)}$	0.946	0.001	$1^{(-)},3^{(-)},4^{(-)}$	0.225	0.064	$2^{(+)},4^{(+)},5^{(+)}$	0.397	0.110	$1^{(-)},2^{(+)},3^{(-)}$	0.587	0.063	$1^{(-)},3^{(-)}$
DIS	f_1,f_2	0.171	0.018	$2^{(+)},4^{(+)},5^{(+)}$	0.257	0.010	$1^{(-)},4^{(+)}$	0.201	0.031	$4^{(+)},5^{(+)}$	0.686	0.064	$1^{(-)},2^{(-)},3^{(-)},5^{(-)}$	0.204	0.116	$1^{(-)},3^{(-)},4^{(+)}$
	f_3,f_4	0.234	0.031	$4^{(+)}$	0.273	0.041	$3^{(-)},4^{(+)},5^{(-)}$	0.198	0.017	$2^{(+)},4^{(+)}$	0.606	0.054	$1^{(-)},2^{(-)},3^{(-)},5^{(-)}$	0.228	0.059	$2^{(+)},4^{(+)}$
	f_5,f_6	0.221	0.026	$4^{(+)}$	0.263	0.070	$3^{(-)},4^{(+)},5^{(-)}$	0.205	0.055	$2^{(+)},4^{(+)}$	0.633	0.158	$1^{(-)},2^{(-)},3^{(-)},5^{(-)}$	0.203	0.054	$2^{(+)},4^{(+)}$

Investigations for images with 2 features. Comparison in terms of mean, standard deviation and statistical test for considered indicators.

SALA 2016 – Art Exhibition, Australia



SALA 2016 – Adelaide, Australia



SALA 2018 – Art Exhibition, Australia

Conclusions

- Evolutionary algorithms provide a flexible approach to the creation of artistic work.
- A lot of algorithmic approaches have been shown to be able to create artistic work.
- Evolutionary process itself can be used to create artistic digital work.
- Random processes exhibit in interesting sources of inspiration.
- Evolutionary diversity optimization can be used to create a diverse set of designs that vary with respect to given features.

Thank you!

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