Aneta Neumann and Frank Neumann

Evolutionary computation for digital art

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Evolutionary Computation for Digital Art

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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
- Quasi-random Image Animation
- Evolutionary Image Composition
- Evolutionary Image Diversity Optimization
- Discrepancy-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 Darwinian 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.

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

- Gary Greenfield (1998-2005) evolved simulated ant and robot parameters, and investigated image co-evolution.
- 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
  - Reflectional Symmetry
  - Colorfulness

Aesthetic Measures (den Heijer, Eiben 2014)

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

Neumann, Alexander, Neumann (EvoMusArt 2017)

Evolutionary Image Transition

- 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.

Example Images

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

Image Transition

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 cs =100 and ct=50.

Video: Asymmetric Mutation

Video – Uniform Random Walk

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.

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}.

Video – Biased Random Walk

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_{ij}^r, 1 ≤ r ≤ 3, the rth RGB value of T_{ij} and define

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

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

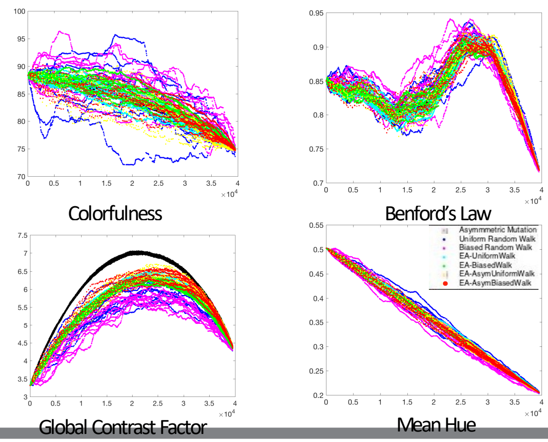
Mutation Based on Random Walks

- 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.

Videos - Biased Random Walk Evolutionary Algorithm



Feature Values During Transition:



SALA 2016 – Art Exhibition

SALA 2016 – Art Exhibition, Australia

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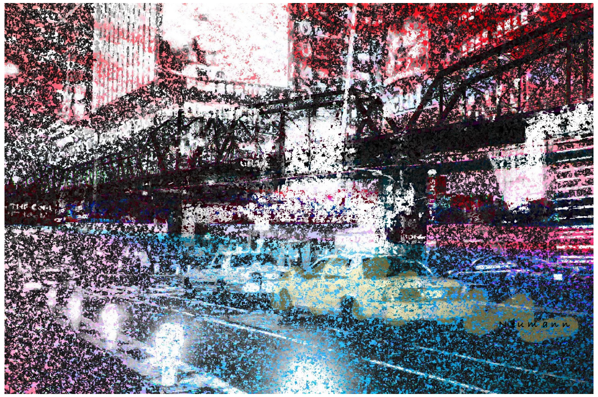

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Quasi-random Transition and Animation

Neumann, Neumann Friedrich (2017)

Quasi-random Walks

- 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.

Example Video: 4 Agents Symmetric Sequences

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).

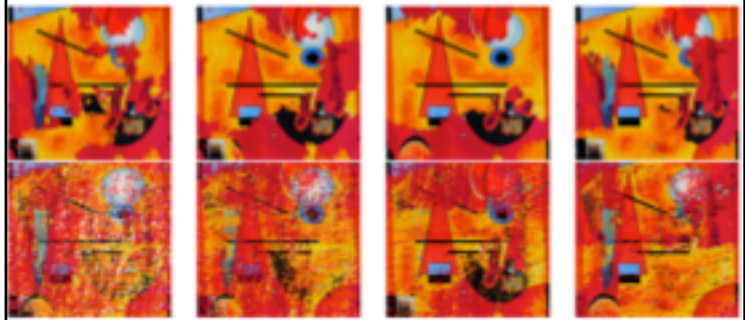
Algorithm

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 $c^k(i,j) \in \{0, \ldots, |S^k|\}$, $1 \leq i \leq m$, $1 \leq j \leq n$.

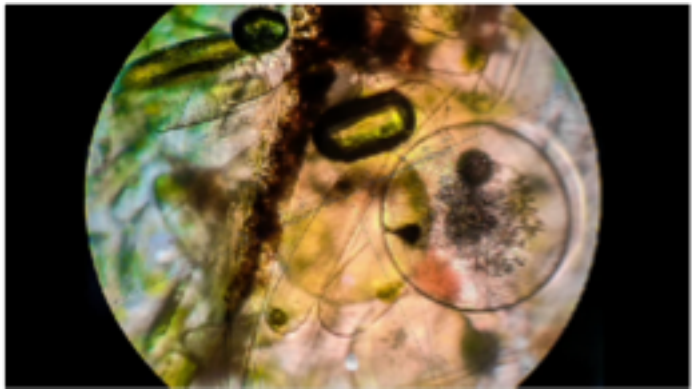
$X \leftarrow Y$
for each agent k, $1 \leq k \leq r$ **do**
    choose $P^k \in m \times n$ and set $X(P^k) := I^k(P^k)$.
end for
$t \leftarrow 1$
while $(t \leq t_{\max})$ **do**
    for each agent k, $1 \leq k \leq r$ **do**
        Choose $\hat{P}^k \in N(P^k)$ according to $S_k(c(P^k))$.
       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

2 Agents Symmetric and Asymmetric Sequences



Example Video: 4 Agents Asymmetric Sequences

Video Quasi-random Walks



Evolutionary Image Composition

Neumann, Szpak, Chojnacki, Neumann (GECCO 2017)

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.

Evolutionary Image Composition Using Feature Covariance Matrices

- 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.

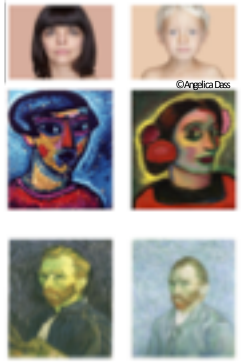
Algorithm 1 $(\mu + 1)$ GA for evolutionary image composition

```
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_c
            Y ← RandomWalkMutation(X, Z, t_c)
        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.
```

$$f(X,S,T) = \sum_{(c,d)\in\mathcal{R}} \left(w^S_{(c,d)} \operatorname{dist}\left(\Lambda^X_{R_{c,d}}, \Lambda^S_{R_{c,d}}\right) + w^T_{(c,d)} \operatorname{dist}\left(\Lambda^X_{R_{c,d}}, \Lambda^T_{R_{c,d}}\right) \right).$$

#1

covariance-based fitness function

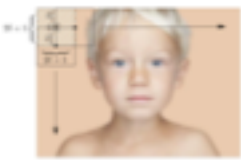


#1
pixel-based mutation

#2
self adaptive random walk mutation

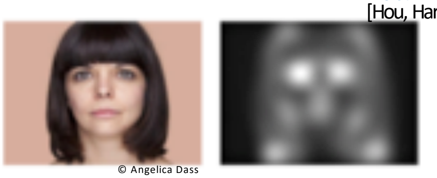
[A. Neumann, B.Alexander, F. Neumann, EvoMusArt 2017]
[B. Doerr, C. Doerr, GECCO 2015]

#3
square region of interest



$$\mathcal{R} = \left\{ (c,d) \;\middle|\; \begin{array}{l} c = (l+1)\cdot p l,\ p = 0,1,\ldots,\left\lceil \frac{m-l}{l} \right\rceil - 1 \\ d = (l+1)\cdot q l,\ q = 0,1,\ldots,\left\lceil \frac{n-l}{l} \right\rceil - 1 \end{array} \right\}$$

#4
saliency mask
[Hou, Harel, Koch, IEEE 2012]



#5
set of features

$$\textbf{Set 1: } \left[i, j, r, g, b, \sqrt{\left(\tfrac{\partial I}{\partial x}\right)^2 + \left(\tfrac{\partial I}{\partial y}\right)^2}, \tan^{-1}\left(\left|\tfrac{\partial I}{\partial y}\right| / \left|\tfrac{\partial I}{\partial x}\right|\right)\right]^T;$$
$$\textbf{Set 2: } [i, j, h, s, v]^T;$$
$$\textbf{Set 3: } \left[h, s, v, \sqrt{\left(\tfrac{\partial I}{\partial x}\right)^2 + \left(\tfrac{\partial I}{\partial y}\right)^2}, \tan^{-1}\left(\left|\tfrac{\partial I}{\partial y}\right| / \left|\tfrac{\partial I}{\partial x}\right|\right)\right]^T.$$

Experiments

- Investigate the impact of different region covariance features on the resulting images
- Discover how different weighting schemes for covariance matrices influence the results
- Understand the influence that the distance measures have on the final results

Impact of Different Features

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 set to 0.25, 0.5 and 0.75 and 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.

SALA 2017 Art Exhibition Adelaide, Australia

Evolutionary Diversity Optimisation for Images

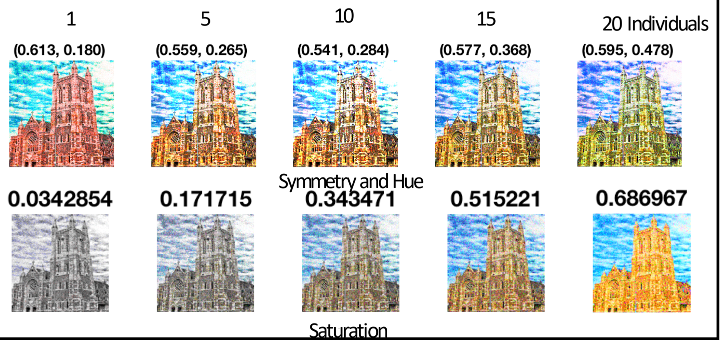
Alexander, Kortman, A. Neumann (GECCO 2017)

Diversity

- Majority of approaches consider diversity in the objective space.
- Ulrich/Thiele considered diversity in the search space (Tamara Ulrich's PhD thesis).
- Diversity with respect to other properties (features) could be useful in various domains.
- Goal: Compute a set of good solutions that differ in terms of interesting properties/features.

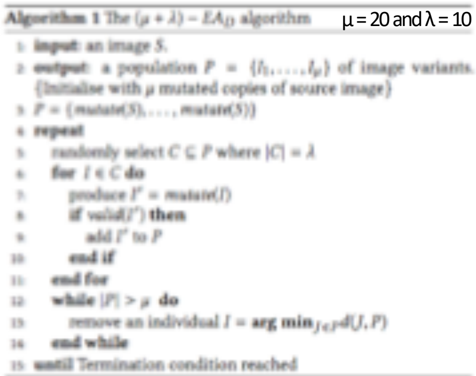
Key Idea

- 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

- We use $(\mu + \lambda)-EA_D$ 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

$\mu = 20$ and $\lambda = 10$

```
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

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

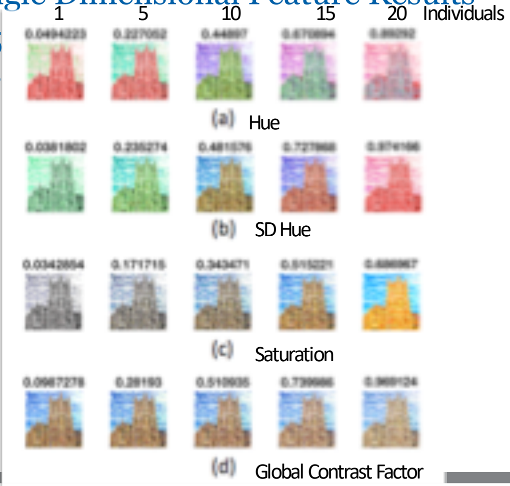
$$d_{f_i}(I_i, P) = (f(I_i) - f(I_{i-1})) \times (f(I_{i+1}) - f(I_i))$$

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

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

Single Dimensional Feature Results

#5 features



Two-Dimensional Feature Experiments

a) Symmetry and Hue 20 Individuals

Discrepancy-Based Evolutionary Diversity Optimization for Images

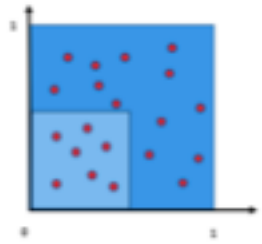
A. Neumann, Gao, Doerr, F. Neumann, Wagner (GECCO 2018, Wednesday 11:55 in GA track)

Discrepancy-Based Evolutionary Diversity Optimization

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

Motivation and Background

Given a set of points $X := \{s^1, \dots, s^n\}$ with $S = [0, 1]^d$, $s^1, \dots, s^n \in S$



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

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

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

Discrepancy-Based Evolutionary Diversity Optimization for Images

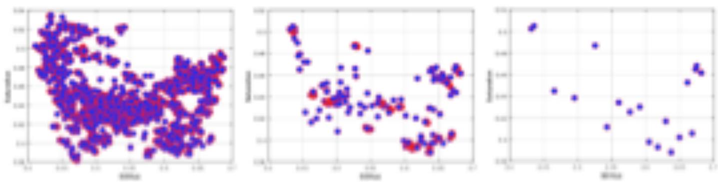
#1

Self-Adjusting Offset Random Walk Mutation

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

#2

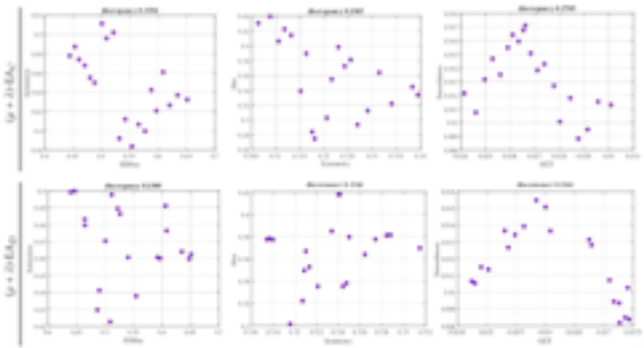
Features



Discrepancy-Based Evolutionary Diversity Optimization for Images

#4

Results



Discrepancy-Based Evolutionary Diversity Optimization for Images

#4

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)	0.2914	0.3254	0.0595	$2^{(-)},3^{(-)}$	0.1272	0.2058	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	$2^{(-)},3^{(-)}$	0.1365	0.2025	0.0538	$1^{(+)}$	0.1457	0.1900	0.0254	$1^{(+)}$
(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	$1^{(+)}$

For details come to the paper presentation
Wednesday 11:55 in GA track

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!

Literature

- R. Dawkins (1986): The Blind Watchmaker - Why the Evidence of Evolution Reveals a Universe without Design, W. W. Norton & Company.
- W. Latham (1985): *Black Form Synth*. Offset lithograph, E.293-2014, Victoria and Albert Museum, London, UK. ht[redacted]
- K. Sims (1991): Artificial evolution for computer graphics. In Proc. Conf. Computer Graphics and Interactive Techniques (SIGGRAPH '91). ACM Computer Graphics, 25(4): pp. 319–328. [redacted]
- K. Sims (1997): *Galápagos*. Installation at the NTT InterCommunication Center in Tokyo, Japan. [redacted]
- S. Todd and W. Latham (1992): Evolutionary Art and Computers. Academic Press, London.
- T. Unemi (1999): SBART2.4: Breeding 2D CG Images and Movies, and Creating a type of Collage. In: The International Conference on Knowledge- based Intelligent Information Engineering Systems, pp. 288– 291. h[redacted]

Literature

- H. Takagi (2001): Interactive evolutionary computation: fusion of the capabilities of EC optimization and human evaluation. Proc. IEEE 89(9), pp. 1275–1296. h[redacted]
- P. Machado and A. Cardoso (2002): All the truth about NEvAr. Appl. Intell. 16, 2, pp. 101–118. h[redacted]
- G. Greenfield (2006): Robot paintings evolved using simulated robots. In Workshops on Applications of Evolutionary Computation, pages 611–621. Springer, h[redacted]
- S. Draves (2005): The electric sheep screen-saver: A case study in aesthetic evolution. EvoMUSART. Vol. 3449 of Lecture Notes in Computer Science. Springer, pp. 458–467. h[redacted]
- D. Hart (2007): Toward greater artistic control for interactive evolution of images and animation. In Applications of Evolutionary Computing, EvoWorkshops 2007, volume 4448 of Lecture Notes in Computer Science, Springer, pp. 527–536. htt[redacted]
- T. Kowaliw, A. Dorin, and J. McCormack (2012): Promoting Creative Design in Interactive Evolutionary Computation. IEEE Trans. Evolutionary Computation 16(4), pp. 523–536. h[redacted]
- J. Graf and W. Banzhaf (1995): Interactive evolution of images. In Proc. Conference on Evolutionary Programming, pp. 53–65.

Literature

- E. den Heijer and A. E. Eiben (2014): Investigating aesthetic measures for unsupervised evolutionary art. Swarm and Evolutionary Computation 16, pp. 52–68. h[redacted]
- A. Neumann, B. Alexander, and F. Neumann (2017): Evolutionary Image Transition Using Random Walks. In: Computational Intelligence in Music, Sound, Art and Design, EvoMUSART 2017, Lecture Notes in Computer Science, 230-245. htt[redacted] 2[redacted]
- A. Neumann, B. Alexander, and F. Neumann (2016): The Evolutionary Process of Image Transition in Conjunction with Box and Strip Mutation. In: Neural Information Processing, ICONIP 2016. [redacted]
- A. Neumann, F. Neumann, and T. Friedrich: Quasi-random Agents for Image Transition and Animation. In: submitted for publication, CoRR abs/1710.07421. Submitted for publication. h[redacted]
- A. Neumann, Z. L. Szpak, W. Chojnacki, and F. Neumann (2017): Evolutionary Image Composition Using Feature Covariance Matrices. In: Genetic and Evolutionary Computation Conference, GECCO 2017, ACM Press, 817-824. htt[redacted]
- K. Matkovic, L. Neumann, A. Neumann, T. Psik, W. Purgathofer (2005): Global Contrast Factor - a new approach to image contrast. Computational Aesthetics. 2005:159–168 h[redacted]

Literature

- D. Hasler, S.E. Suesstrunk (2003): Measuring colorfulness in natural images. In Electronic Imaging 2003, pages 87–95. International Society for Optics and Photonics, h[redacted]
- J.-M. Jolion (2001): Images and Benford's law. Journal of Mathematical Imaging and Vision, 14(1):73–81, [redacted]
- B. Alexander, J. Kortman, and A. Neumann (2017): Evolution of Artistic Image Variants Through Feature Based Diversity Optimisation. In: Genetic and Evolutionary Computation Conference, GECCO 2017, ACM Press, 171-178. htt[redacted]
- A. Neumann, W. Gao, C. Doerr, F. Neumann, M. Wagner (2018): Discrepancy-Based Evolutionary Diversity Optimization. In: Genetic and Evolutionary Computation Conference, GECCO 2018, ACM Press h[redacted]