On the Use of Colour-Based Segmentation in Evolutionary Image Composition

Aneta Neumann, Frank Neumann
The University of Adelaide,
Australia

Our Goal and Key Idea

- Produce artistic images using evolutionary computation methods
- Create a composition of two images using a region covariance descriptor and colour-based segmentation based on K-Means clustering
- Incorporate region covariance descriptors and a weighting of interesting regions of the two images into fitness function

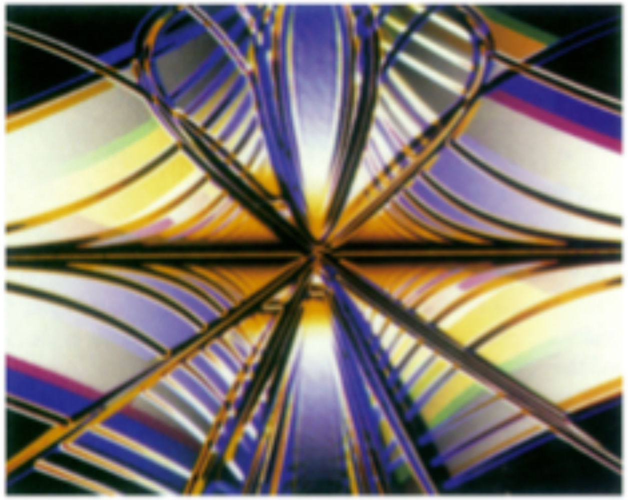
This talk: A contribution to evolving artistic image composition

Outline

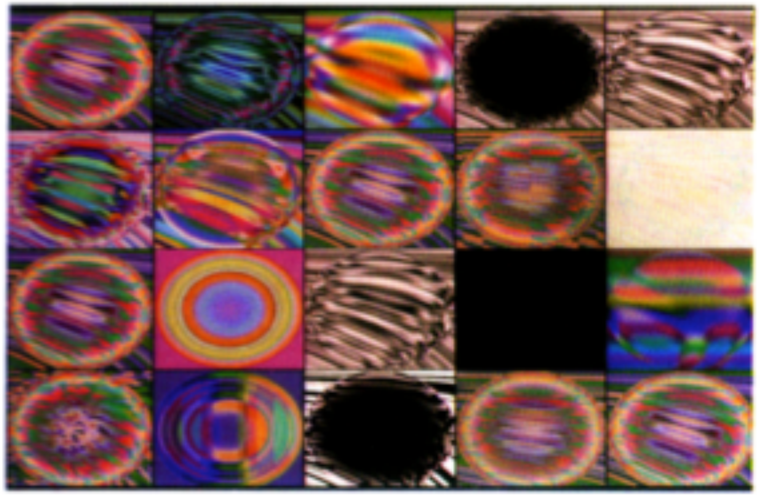
1. Motivation and background
2. Covariance-based fitness function
3. (μ + 1) GA for evolutionary image composition
4. Colour-based image segmentation for evolutionary image composition (SEIC)
5. Experiments: impact of colour-based segmentation, impact of distance measures, impact of different sizes of the regions
6. Conclusions

Motivation and Background (Sims, 1991)

- In Karl Sims (1991) published a SIGGRAPH paper explaining EC system using evolving expressions

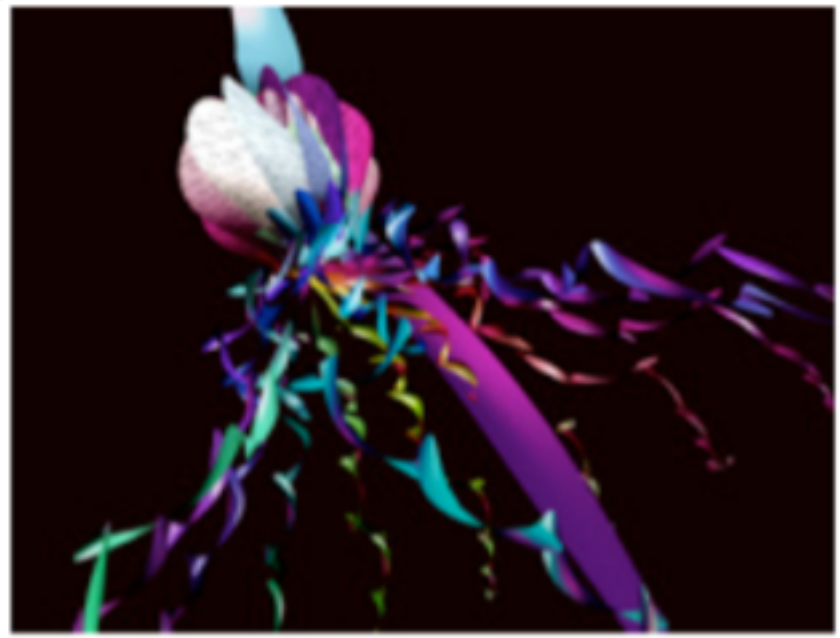


```
(round (log (+ y (color-grad
(round (+ (abs (round (log (+
y (color-grad (round (+ y (log
(invert y) 15.5)) x) 3.1 1.86
#(0.95 0.7 0.59) 1.35)) 0.19)
x)) (log (invert y) 15.5)) x)
3.1 1.9 #(0.95 0.7 0.35)
1.35)) 0.19) x)
```



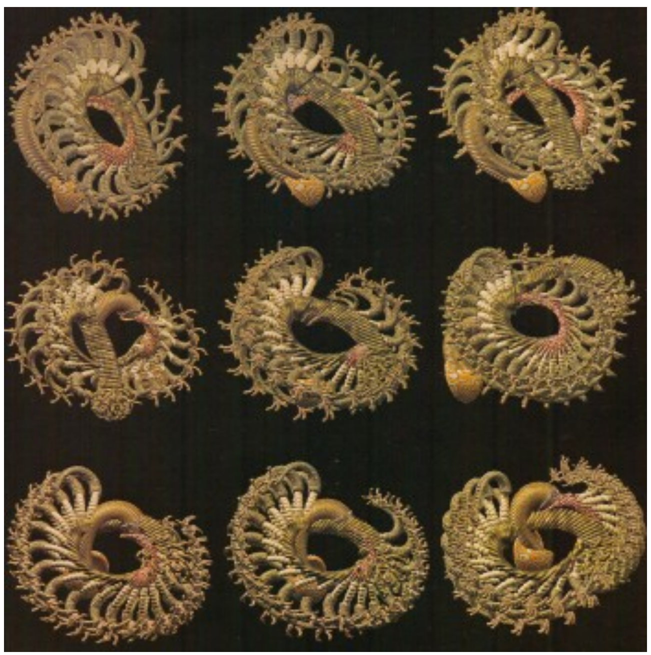
Motivation and Background (Sims, 1997)

- In *Galapagos* Karl Sims (1997) allows the audience to express a preferences



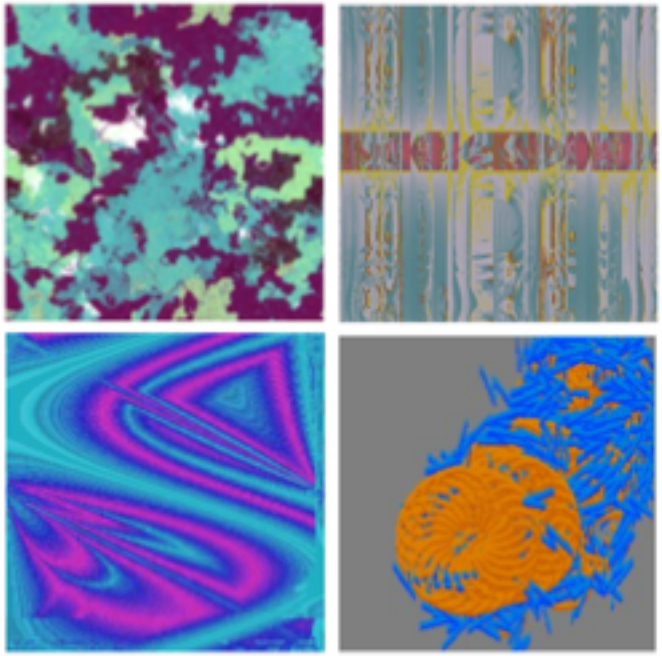
Motivation and Background

- Latham, Todd (1992) combined evolutionary techniques and computer graphics to create artistic images
- Banzhaf, Graf (1995) used interactive evolution to help determine parameters for image morphing



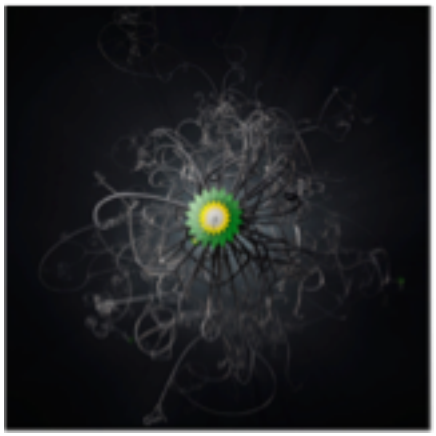
Motivation and Background

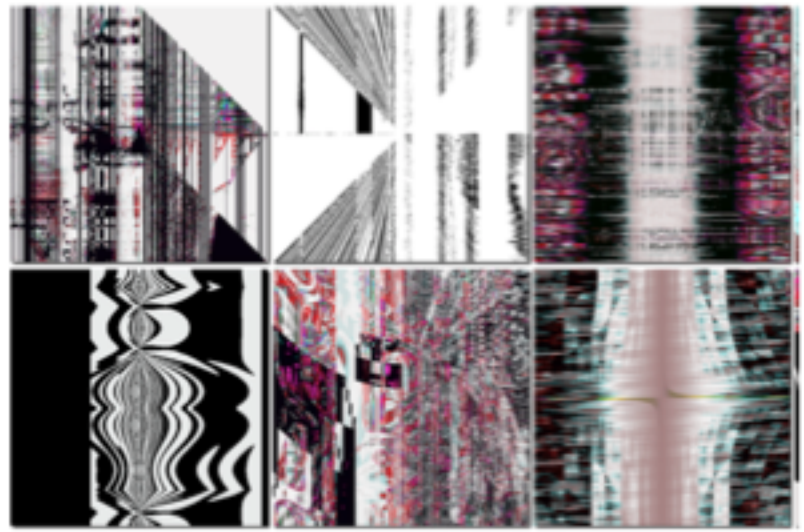
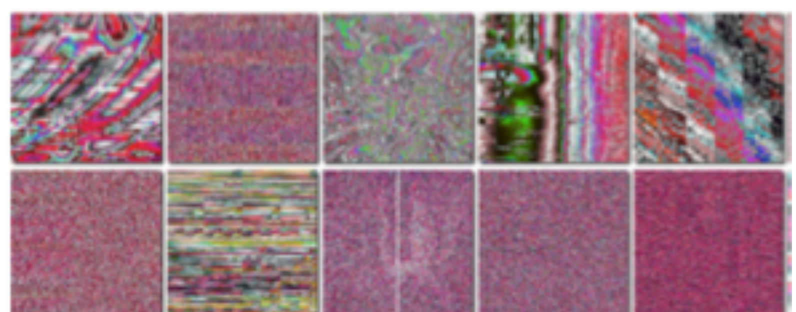
- Gary Greenfield (1998-2005) evolved simulated ant and robot parameters, and investigated image co-evolution
- Scott Draves' *Electric Sheep* (2005) system allows to approve or disapprove of phenotypes



Motivation and Background

- McCormack (2012) created a generative artwork, *Fifty Sisters*, from 3D geometric primitives
- Den Heijer, Eiben (2014) investigated aesthetic measures for unsupervised evolutionary art



Motivation (Gatys, Ecker, Bethge,2016)

Input image

[CVPR 2016, Gatys, Ecker, Bethge]

Evolutionary Image Composition Using Colour-Based Segmentation

- Approach for the composition of images based on Colour-Based Segmentation (SEIC)

  [GECCO 2017, Neumann, Szpak, Chojnacki, Neumann]

- Evolutionary algorithms that create new images based on a fitness function that incorporates feature covariance matrices associated with different parts of the images

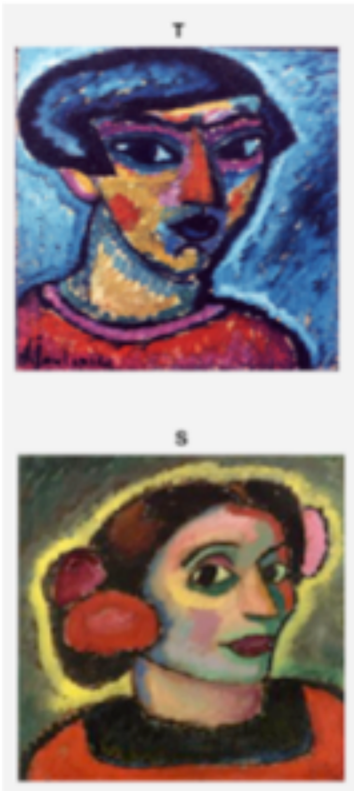
- Population-based evolutionary algorithm with mutation and crossover operators based on random walks

#1

covariance-based fitness function

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

$$c(X) = |c_S(X) - c_T(X)| \leq B,$$



#2
pixel-based mutation

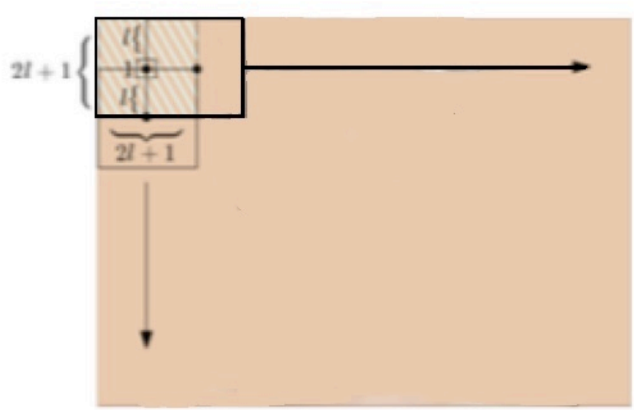
#3
self adaptive random walk mutation

[EvoMusArt 2017, Neumann, Alexander, Neumann]

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

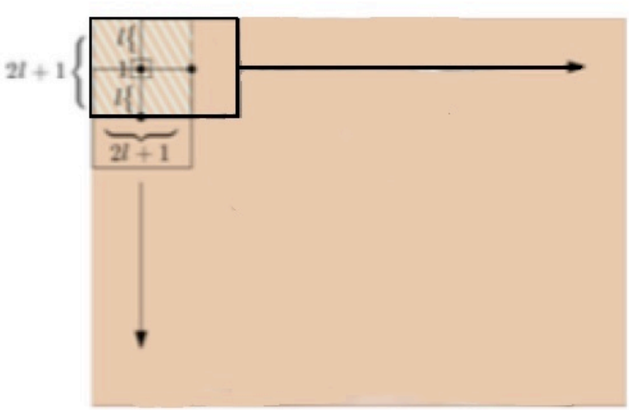
[GECCO 2015, Doerr, Doerr]

#4
square region of interest



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

#3
square region of interest

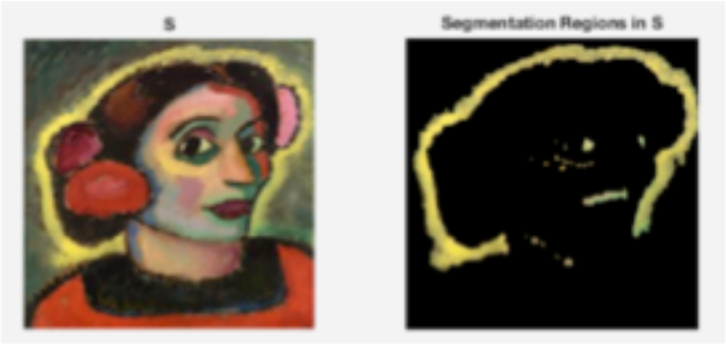


$$\mathcal{G} = \left\{ (c,d) \,\middle|\, \begin{aligned} c &= (l+1) + pl,\; p = 0, 1, \ldots, \left\lfloor \frac{m-l}{l} \right\rfloor - 1 \\ d &= (l+1) + ql,\; q = 0, 1, \ldots, \left\lfloor \frac{n-l}{l} \right\rfloor - 1 \end{aligned} \right\}$$

#4
saliency mask

[IEEE 2012, Hou, Harel, Koch]

#4
segmentation-based mask



#5
set of features

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

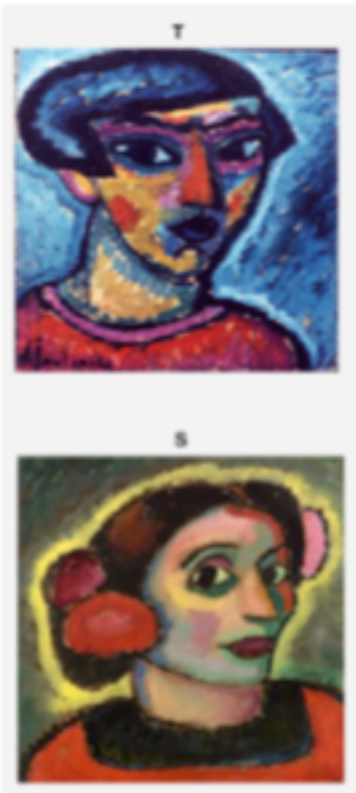
Set 2: $[i, j, h, s, v]^{\mathsf{T}}$;

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

Experiments

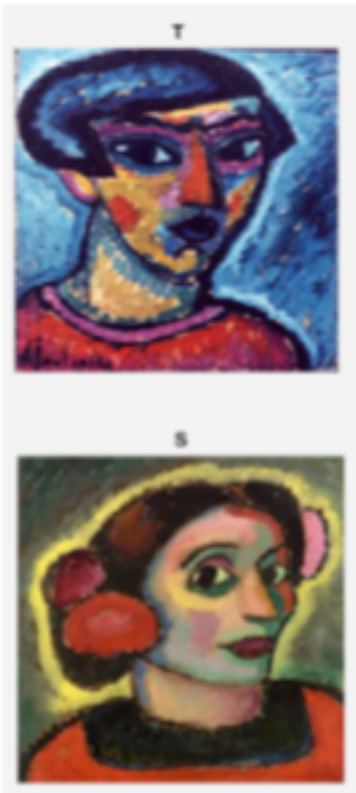
- Investigate the impact of different region covariance features on the resulting images
- Discover how different weighting schemes for covariance matrices influence the results
- Understand the influence that the distance measures have on the final results

Impact of Colour-Based Segmentation



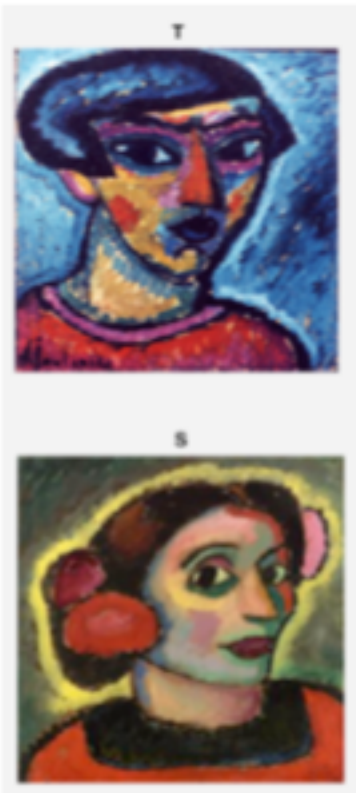
Population of evolved images S and T after 2000 generations using K-Means segmentation and yellow-coloured clustering schema (top), and one pair of evolved images S and T after 2000 generations using the saliency weighting schema from [GECCO 2017, Neumann et al.] (bottom).

Impact of Distance Measures



Evolved Images with K-Means segmentation with different distance measures. Row 1 corresponds to distance measures cityblock and row 2 to cosine, respectively.

Impact of Different Sizes of the Regions



Evolved Images with K-Means segmentation with different windows sizes. Rows 1, 2, 3 and 4 correspond to windows size 5, 20, 40 and 120, respectively.

Feature-based Analysis

TABLE I

RESULTS OF AESTHETIC MEASUREMENTS USING PREVIOUSLY EIC APPROACH WITH SALIENCY WIGHTING AND COLOUR-BASED SEIC USING ECLUE.1 BLUE-COLOURED, ECLU.2 YELLOW-COLOURED, ECLUE.3 RED-COLOURED SPACES, CITYBLOCK AND COSINE DISTANCE MEASURES RESPECTIVELY. NOTE BOLD TEXT VALUES HAVE THE HIGHEST SCORE COMPARING THE TWO APPROACHES.

Features	**Saliency [1] mean**	**Saliency std**	ECLU.1 mean	ECLU.1 std	ECLU.2 mean	ECLU.2 std	ECLU.3 mean	ECLU.3 std	city. mean	city. std	cosine mean	cosine std
Glob. Contrast Factor	0.0395	0.0004	**0.0396**	0.0004	0.0391	0.0015	0.0393	0.0006	0.0395	0.0002	**0.0396**	0.0003
Ross Bell Curve	0.0129	0.0004	**0.0164**	0.0030	**0.0174**	0.0049	0.0168	0.0026	**0.0149**	0.0012	**0.0147**	0.0001
Benford's Law	0.8471	0.0170	**0.8660**	0.0207	0.8464	0.0594	**0.8674**	0.0141	**0.8513**	0.0116	**0.8652**	0.0197
Saturation	0.3375	0.0067	**0.3433**	0.0284	0.3311	0.0441	**0.3403**	0.0286	**0.3441**	0.0193	**0.3572**	0.0339
Ref.Symmetry	0.4069	0.0040	**0.4168**	0.0178	**0.4324**	0.0511	**0.4132**	0.0188	**0.4075**	0.0086	0.4058	0.0078
Hue	0.3295	0.0064	0.2855	0.1143	0.2869	0.0792	0.2790	0.1011	0.3129	0.0534	**0.3469**	0.0834
Symmetry	0.8244	0.0025	0.8231	0.0084	0.8220	0.0110	0.8195	0.0074	0.8199	0.0034	0.8193	0.0060
SDHue	0.7010	0.0097	0.6206	0.1031	0.6699	0.0401	0.6146	0.0931	0.6607	0.0356	0.6800	0.0333
Smoothness	0.9451	0.0010	**0.9504**	0.0047	0.8716	0.1273	**0.9505**	0.0044	**0.9477**	0.0025	**0.9486**	0.0014

Feature-based Analysis

TABLE II
RESULTS OF AESTHETIC MEASUREMENTS USING COLOUR-BASED K-MEANS SEIC APPROACH FOR WINDOW SIZE 5, 20, 40, 120, THE IMAGE S AND T, RESPECTIVELY. NOTE BOLD TEXT VALUES HAVE THE HIGHEST SCORE COMPARING THE TWO APPROACHES.

Features	W-5 mean	W-5 std	W-20 mean	W-20 std	W-40 mean	W-40 std	W-120 mean	W-120 std	Image S	Image T
Glob. Contrast Factor	0.0393	0.0005	0.0392	0.0002	0.0393	0.0004	**0.0400**	0.0002	0.0198	0.0212
Ross Bell Curve	**0.0230**	0.0103	**0.0172**	0.0029	**0.0171**	0.0035	**0.0136**	0.0003	0.9897	0.5715
Benford's Law	**0.8555**	0.0129	**0.8504**	0.0097	**0.8584**	0.0115	**0.8534**	0.0111	0.7940	0.7752
Saturation	**0.3614**	0.0259	**0.3430**	0.0213	**0.3457**	0.0292	0.2207	0.1184	0.4564	0.5844
Ref.Symmetry	0.3897	0.0412	**0.4085**	0.0161	**0.4135**	0.0167	**0.4071**	0.0004	0.2295	0.1684
Hue	0.2877	0.1160	0.2709	0.1006	0.2843	0.1236	0.3012	0.0017	0.1875	0.6329
Symmetry	0.8200	0.0075	0.8203	0.0066	0.8225	0.0063	0.8224	0.0010	0.8006	0.7495
SDHue	0.6231	0.0837	0.6322	0.0830	0.6070	0.1079	0.6814	0.0126	0.4623	0.4697
Smoothness	**0.9518**	0.0042	**0.9504**	0.0044	**0.9518**	0.0053	0.9426	0.0010	0.9624	0.9427

SALA 2017 Art Exhibition
Adelaide, Australia

Conclusions

- Introduced how to use colour-based image segmentation within the evolutionary image composition approach given in [GECCO 2017, Neumann, Szpak, Chojnacki, Neumann]

- Shown that the use of colour-based segmentation allows to create composed images based on their colour characteristics have a higher value in various aesthetic feature compared to the previous evolutionary image composition based on saliency masks

- Compared the final populations showing the resulting images with respect to different parameters and studied there effects on the aesthetic appearance of the images

For any further questions please contact:

Aneta.Neumann@adelaide.edu.au

Frank.Neumann@adelaide.edu.au