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

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***Abstract*—Evolutionary algorithms have been widely used in the area of creativity in order to help create art and music. We consider the recently introduced evolutionary image composition approach based on feature covariance matrices [1] which allows composing two images into a new one based on their feature characteristics. When using evolutionary image composition it is important to obtain a good weighting of interesting regions of the two images. We use colour-based segmentation based on K-Means clustering to come up with such a weighting of the images. Our results show that this preserves the chosen colour regions of the images and leads to composed images that preserve colours better than the previous approach based on saliency masks [1]. Furthermore, we evaluate our composed images in terms of aesthetic feature and show that our approach based on colour-based segmentation leads to higher feature values for most of the investigated features.**

I. Introduction

Bio-inspired computing methods have been widely applied in the area of digital art [2], [3] and several frameworks have been introduced to create artworks based on evolutionary computation methods [4], [5] and machine learning [6]–[8]. In early years, evolutionary algorithms have been used for the generation of digital art based on the potential of Darwinian variations [9]–[12]. By following these steps computer graphics and evolutionary methods have been successful combine to create artworks [13]–[18]. In order to judge the quality of such artistic images produced by evolutionary computation methods, aesthetic features have been introduced to measure their properties in an objective way [19]–[21]. Furthermore, image features play a crucial role in computer vision to classify images according to their properties [22]–[24].

Recently, evolutionary processes have been used to create artistic images and videos through evolutionary image transition [25]. In evolutionary image transition, an image S is transitioned into a target image T by the evolution process of an evolutionary algorithm. This process has been adapted to the composition of two images based on covariance features [1]. In evolutionary image composition (EIC), a composition of two images is created by evolving an image that is similar to the given two images S and T and an error function that takes into account the similarity of the resulting images to S and T in terms of a covariance feature-based distance measure. An

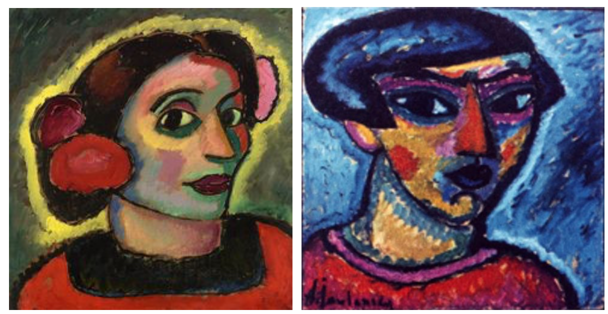

Fig. 1. Image S (Spanish Woman, 1911 by Alexej von Jawlesnky) and image T (Head in blue, 1912 by Alexej von Jawlesnky).

important aspect to create visually pleasing compositions of images is good method to characterize important regions of the given images as that the composition takes into account these aspects. In [1], it has been shown that the use of different weightings in the fitness function plays a crucial role in obtaining good image compositions.

In this paper, we investigate the use of image segmentation methods in evolutionary image composition. We introduce segmentation-based evolutionary image composition (SEIC) which makes use of image segmentation methods to come up with suitable weightings of different regions of the given images in order to produce a good composition of the images. Our segmentation method uses the importance of colours in order to come up with good weightings. The perception of colour is important for the perception of images [26] and the use of colours can be seen as a product of our language [27] and culture [28].

We use image segmentation based on K-Means which converts a given colour image as shown in Figure 1 into a *Lab* colour space image and separates the positions of a set of colours. The segmentation is then used in the image composition process in order to come up with images that minimize the error in terms of the weighted covariance featured-based error function where weights are set according to the colour-based segmentation.

We evaluate our approach by feature-based analyses which reveal that aesthetic features values for almost all the images

Fig. 2. Images with corresponding segmentations regions with blue-coloured schema in image T and yellow-coloured schema in image S (from top left, respectively).

are higher using our segmentation approach compared to the evolutionary image composition approaches investigated in [1].

The paper is structured as follows. In Section II, we introduce the evolutionary image composition approach that we investigate. Section III-A introduces the different image segmentation methods that we use to obtain the weighting for evolutionary image composition. In Section IV, we report our experimental results and compare the different weightings based on the investigated image segmentation methods. Finally, we finish with some conclusions.

II. Evolutionary Image Composition based on Feature Covariance Matrices

Evolutionary image composition creates a composition of two given images taking into account important properties of these images. Given two images, $S = (S_{ij})$ and $T = (T_{ij})$ of size $m \times n$, it produces a new image $X = (X_{ij})$ of the same size, that is a mixture of the input images, i.e. $X_{ij} \in \{S_{ij}, T_{ij}\}$ for each $1 \leq i \leq m$ and each $1 \leq j \leq n$.

We investigate the evolutionary image composition approach based on a using feature covariance matrices given in [1]. The approach uses a $(\mu+1)$-EA which aims to produce a set of μ images by mutation and crossover based on random walks. For a detailed description of the algorithm, we refer the reader to [1].

The key part of the image composition approach in [1] is the used fitness function, which is very flexible and can take various features of the images into account. Given two images S and T both of size $m \times n$, the goal is to minimize the fitness of a composed image X of size $m \times n$ given by

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

The fitness function f measures the error of X with respect to S and T. Here dist is a distance function, and $w^S_{(i,j)}$ and $w^T_{(i,j)}$ are weights for S and T associated with pixel (i,j), $1 \leq i \leq m$, $1 \leq j \leq n$.

$\mathcal{R}_{(c,d)}$ denotes a region of the image and $\Lambda^I_{(i,j)}$ the local covariance matrix of image I centered at pixel (i,j). For a detailed description of the the covariance feature-based fitness function, we refer the reader to [1].

As in [1], we consider square regions in a grid-like manner determined by parameter l called the half-window size. The regions $\mathcal{R}_{(c,d)} = \{(i,j) \mid |i-c| \leq l, |j-d| \leq l\}$ are squares of size $(2l+1)\times(2l+1)$ centered at points (c,d) given by a grid of pixels $\mathcal{G}$. Formally, the grid is defined as

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

which results in half-overlapping square regions.

In order to make sure that each composed image X has a certain number of pixels from S and T the following constraint is used. Let $c_S(X) = |\{X_{ij} \mid X_{ij} = S_{ij}\}|$ be the number of pixels in X that are set to S and $c_T(X) = |\{X_{ij} \mid X_{ij} = T_{ij}\}|$ be the number of pixels where X and T agree. The fitness function f is minimized subject to the constraint

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

which says that the number of pixels in X belonging to S and T can differ by at most B.

In [1] has been shown that the chosen distance function, the chosen features, and the weighting of the different pixels of the image play a crucial role for the outcome of the considered evolutionary image composition approach. In particular, a good weighting of regions of interest in the two given images S and T is crucial and the best results have been obtained in [1] by using a saliency mask to obtain the weights $w^S_{(i,j)} \in \mathbb{R}^{m\times n}$ and $w^T_{(i,j)} \in \mathbb{R}^{m\times n}$ for the given images S and T. We will explore the use of image segmentation methods to come up with suitable weightings of the different regions.

III. Colour-based Image Segmentation for Evolutionary Image Composition

Clustering is considered an important unsupervised machine learning problem. Data elements are partitioned into clusters that represent approximate collections of data elements based on a distance function. Clustering analysis has found many applications in areas such as data mining [29], [30] and data compression [31].

It has been shown that different weighting schemes of the image have an important role in determining the weighting of the final outcome of the evolutionary image composition. In this paper, we investigate different weightings of regions using the segmentation method. We denote two given images S and T of the size $m \times n$ that we can randomly select from a given image database. We utilize different segmentation masks w^S and w^T that are calculated for both image S and T in order to distinguish different images using evolutionary image composition. We use the weighting matrices $w^S \in \mathbb{R}^{m\times n}$ and $w^T \in \mathbb{R}^{m\times n}$ that are associated with images S and T. The weights are obtained by colour-based K-Means segmentation methods which we describe in the following.

A. K-Means Clustering for Colour-based Segmentation

K-Means is one of the popular algorithms for clustering unsupervised data [22]. We use Lloyd's algorithm, which is best known as the K-Means algorithm, to solve the K-Means clustering problem [32]. The algorithm is based on the observation that the optimal distribution of a center occurs at the centroid of the associated cluster [33]. An important component of a clustering problem is the distance between data points. In order to group similar points together, we can use the *Squared Euclidean Distance* metric (or any other suitable distance metric) to calculate the distance between points.

Given n data points, the data is partitioned in k clusters where k is a parameter chosen by the user. Each cluster has a cluster center which is given by the mean of the points in the cluster. The algorithm assigns each of the n data points to the closest cluster center. Centers are updated by taking the mean of each cluster and the process is iterated. The K-Means algorithm aims to find the positions i, $i = 1, \ldots, k$ on the cluster which minimize the distance from those points to the cluster.

In Figure 3, we visualize the *Lab* colour space for images S and T. This enables us to quantify the visual differences. We show the adequate cluster assignments and plot the silhouette values from the clustered data for each image. Silhouette values from both images give us information on how similar these points are compared to other points in its own and the other two clusters.

A key concept for our approach is the use of the K-Means clustering algorithm for colour-based segmentation in order to separate various colours in an automated procedure. This happens by using the *Lab* colour space in the K-Means clustering algorithm. The *Lab* colour space is expressed by a luminosity 'L', also called the brightness layer, the chromaticity layer 'a' that specifies where colours take place along the red-green axis, and the chromaticity layer 'b' which determines where colours take place along the blue-yellow axis. The steps of the processes are as follows.

Firstly, we convert the image from *RGB* colour space to *Lab* colour space. Then, we classify the colours in the $a \times b$ space using K-Means clustering. The color information remains in the $a \times b$ space. We use K-Means to cluster the objects into three clusters using the Euclidean distance metric. As input into the K-Means algorithm we consider our objects that are

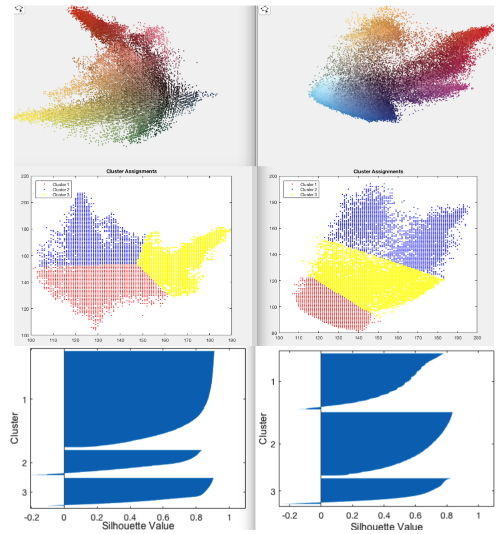

Fig. 3. *Lab* colour classes of image S and image T, cluster assignments, and silhouette values from clustered data (from top left, respectively).

the pixels of the given image with a and b values. We have to specify the number of clusters that we want to use in K-Means. For our experiments, we use $K = 3$ which results in 3 clusters.

Afterwards, we label every pixel in the image with using the results from K-Means with its own index corresponding to a cluster. We separate objects in the image by color. Note that for our setting the results consist of three images as we set $K = 3$ in the K-Means algorithm.

For our experiments, we use the K-means segmentation method implemented in Matlab using the Statistics and Machine Learning Toolbox [34]. K-Means assigns index numbers 1, 2, and 3 to pixels. The pixels in a particular given image are segmented into three colour spectra: yellow, blue, and red. We do this for the images S and T as shown in Figure 2. In the K-Means algorithm, the procedure uses the squared Euclidean distance metric. The weights for $w^S_{(i,j)}$ and $w^T_{(i,j)}$ are given by the segmented images of a chosen color associated with S and T, respectively.

IV. Experimental Investigations

In this section, we carry out our experimental investigations. We compare the use of colour-based segmentation in evolutionary image composition to the one using saliency masks, which is the best performing method given in [1]. Furthermore, we investigate different parameter settings such as half-window size and different distance measure for evolutionary image composition in conjunction with colour-based segmentation.

We use the pairs of images S and T of the size 240 x 240 pixels for all experiments illustrated in Figure 1. For each set of the experiments, we use the same setting as in [1] and run our algorithm for 2000 generations, t_{max} = 1024, population size of $\mu = 4$, and crossover probability $p_c = 0.2$. Also, the

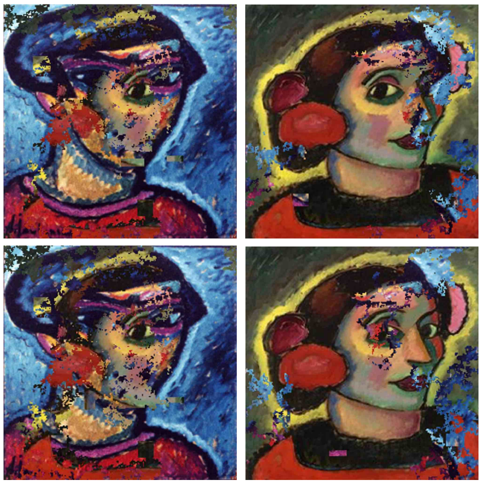

Fig. 4. Two Pairs of evolved images after 2000 generations conducting K-Means segmentation correspond to blue-coloured clustering schema.

upper bound B for the constraint $c(X)$ was assumed as 5000 pixels. At last, we inherited a grid of squared region covariance descriptors ($l = 20$ pixels). We compare the results using colour-based segmentation to the best performing approaches in [1] which uses a saliency mask to obtain the weighting of the images. The experiments have been carried out on the supercomputer Phoenix, on a single node of a Lenovo NeXtScale M5 Cluster including two Intel Xeon E5-2600 v4 series 16 core processors with 64GB of RAM. We run experiments with varying preferences for 30 times to see the effect of different settings on artistic outcomes as described below.

A. Impact of Colour-based Segmentation

We carry out three experiments where our main objective is to identify how the choice of different clustering sets with respect to the *Lab* values affect the final outcome. The *Lab* colour space per definition outlines all colours in the three dimensions [35]. For the experiments, we choose a grid of square region covariance descriptors and set the half-window size $l = 20$ (see Section II). As we can see our population took the evolutionary process differently based on segmentation outcome for the S and T images in comparison to the result presented in the research paper [1]. Our result preserve parts of both images in a special way as the faces are mostly visible and in the background we can only see the second given image. Inspired by the visually different outcomes of our approaches, we investigate two new variants of our algorithm. We employ the K-Means segmentation method and cluster our given images with respect to the red and yellow pixel values in *Lab* colour space. In Figure 5, we see two pairs of evolved images S and T with respect to the yellow- and red-coloured clustering schema. The created images are different to each other and to the one obtained in the first experiment. Interesting properties are occurring on the red-coloured clustering methods, as new forms reveal a surprising composition of the image. In the first row of Figure 6, we see two images created with our approach using the yellow-coloured schema. In the second row, we see two images created with the evolutionary image composition approach using the saliency weighting schema [1]. The images in the first row contain visible yellow parts from the given image. In contrast, images in the second row appear more distracted. We can not recognise the dominant yellow lines. Our algorithm preserves the yellow colour from a given image during the evolutionary processes. This makes it possible to evolve images towards the colour that we wish to be most present in newly created images.

B. Impact of Distance Measures

We now describe experiments carried out when using different distance measure. We use three distance measures for minimization of K-Means segmentation as follows: $square$ $Euclidean$, $cityblock$ and $cosine$ [36]. The K-Means segmentation algorithm computes centroid clusters uniquely for each of the type of distance measurements. At this point, we shortly outline the main properties of the distance measurements. Note x is an observation specified as a row of particular X whilst c is a centroid specified as a row vector. *Squared Euclidean Distance Measures* is a standardized measures where each centroid c is the mean of the points in an explicitly cluster. *Cityblock Distance Measures* is a sum of absolute differences. This means that each centroid c is the component-wise median of the points in the cluster.

Cosine Function Distance Measures is one minus the cosine of the all enclosed angle between points. This means that the particular centroid c is the mean of the points in the cluster [37]. In Figure 7, we see a different series of images where the structure of both images is changed. The distance measures has the primary role in the process of creating the most diverse results.

C. Impact of Different Sizes of the Regions

We now explore how the use of different half-window sizes l influence the generation of images. Figure 8 shows that the window sizes have a clear influence on the final images. We can distinguish between two categories where smaller half-window sizes $l = 5$, 20 produce clearer images. The larger half-window sizes $l = 40, 120$ produce more chaotic patches over different parts of the images. Choosing an appropriate value for the half-window size l can therefore be used to influence the final outcome with the most desired characteristic.

D. Feature-based Analysis

We now analyze the different colour-based segmentation methods for evolutionary image composition with respect to features that measure aesthetic values. Firstly, we analyze the final aesthetic feature values for different colour-based segmentation settings. Furthermore, we compare the different set of parameters against each other.

The set of features we use are, in order of appearance, *Global Contrast Factor* [20], *Ross-Bell-Curve* [38], *Benford's*

Fig. 5. Two pairs of evolved images S and T after 2000 generations using K-Means segmentation. Row 1 correspond to yellow-coloured clustering schema, and row 2 correspond to red-coloured clustering schema.

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

Law [21], *Saturation*, *reflectionary Symmetry* [39], *Mean Hue*, *Symmetry*, *Standart Deviation Hue* and *Smoothness* [40].

We carry out several aesthetic measurements on the final images that were evolve with previous EIC and our colour-based SEIC algorithm. Table I shows the comparison of the results of the evolved images obtained with segmentation in respect to blue, yellow and red colour space, using cityblock and cosine distance measures. Table II shows different window sizes of the covariance regions and the image S and T. The columns in the tables present the mean and standard deviation of the different settings for each feature obtained from the first image from the final population in each run. It should be noted that the algorithms do not have any bias regarding particular images in the population.

The first two columns in Table I give the mean and standard deviation for the approach using the saliency mask [1]. The next three columns give the feature values obtained by using the blue, yellow and the red-based segmentation schema (ECLU.1, ECLU.2, ECLU.3). The last columns in Table I list the features values for cityblock and cosine distance measures. Images evolved with cosine measurement distance and blue colour-based schema achieve by the most of the aesthetic features the highest feature values. However, different aesthetic features give us valuable insights into how the user can create aesthetic images with more control over the evolutionary process.

Table II list the features values obtained by using different window sizes of the covariance regions, the image S and T.

In the Table I and II we see the correlation between different sizes of regions, different distance measures and different colour-based schema segmentation. We can observe that images evolve with the windows size 20, 40, 120, the cosine distance measure and the blue, yellow and red colour-based schema have the highest value for *reflectional Symmetry*.

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

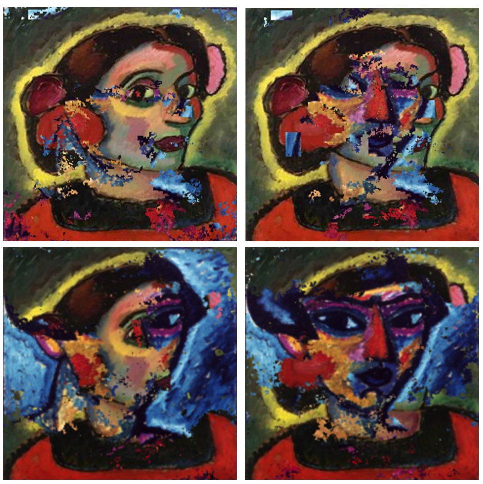

Fig. 6. Population of evolved images S and T after 2000 generations using K-Means segmentation and yellow-coloured clustering schema (top), and one pair of evolved images S and T after 2000 generations using the saliency weighting schema from [1] (bottom).

This mean that regarding this feature the images have also the highest aesthetic value. Similar, the strongest performance for *GCF* achieve images evolved with the windows size 120, the cosine measurements distance and the blue colore-base schema. In contrast, the lowest score for *Benfords'law* has only the yellow colour-based schema. Overall, the images evolve with SIEC have higher *Saturation* values excepts window size 120 and the yellow colour-based schema.

Furthermore, we conduct human subject experiments in order to evaluate the image results presented in our work and in EIC [1]. The goal of the experiment is to gain knowledge about user preferences for images. We carry out a human-based experiment by using Amazon Mechanical Turk [41] with 20 participating users. We present each human two images at a time that correspond to EIC with the saliency weighting schema and the yellow-coloured schema SEIC shown in Fig. 6. The results reveal that the human subjects preferred 95% of the time images created with our SEIC methods. It would be interesting to examine in further study the preferences of the human subject by adding all evolved images with different parameters. It would also be valuable to have more insights into the human subjects in terms of correlation between their preferences, age, education, sex etc.

V. CONCLUSIONS AND FUTURE WORK

Colours play an important role when creating appealing images. We have shown how to use colour-based image segmentation within the evolutionary image composition approach given in [1] and shown that the use of colour-based segmentation allows to create composed images based on their colour characteristics. The evaluation based on the feature-based analysis shows that aesthetic feature values for the images created with our colour-based segmentation approach have a higher value in various aesthetic feature compared to the previous evolutionary image composition based on saliency masks. Additionally, we studied the effects of different parameters in our algorithm on the aesthetic appearance of the images. For future research, it would be interesting to explore more complex fitness functions and their special effect on the evolutionary processes that can produce new abstract images.

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Fig. 7. Evolved Images with K-Means segmentation with different distance measures. Row 1 corresponds to distance measures cityblock and row 2 to cosine, respectively. Note the structure that emerges with the first window set.

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Fig. 8. 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.

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