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Shake it up - Image Decomposition and Rearrangements of Its Constituents

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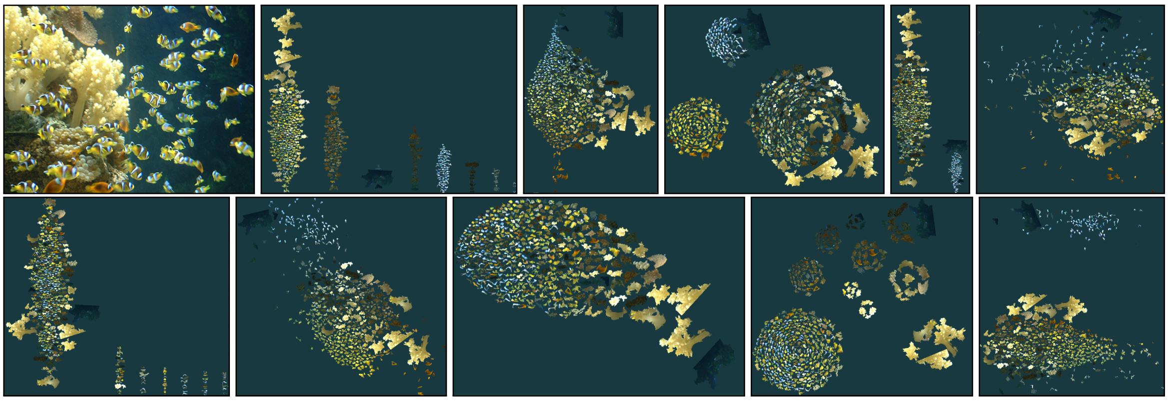

Figure 1: The input image is deconstructed and its constituents are rearranged with examples from force-directed and clustered arrangers. Control features from top left to bottom right in x-y: lightness-hue, spatial sd-green red, spatial sd-yellow blue, size-hue, compactness-green red, compactness-angle, green red-yellow blue, size-spatial sd, size-lightness, color sd-hue. Input image: Personal photograph by the authors.

Abstract

Art aspires to surprise an observer and to offer a different perspective. Changing one's perspective enables a deeper understanding of the examined subject and gives insights that are invisible in the original. We propose a method to automatically deconstruct an image into visually coherent constituents and to rearrange those pieces in a surprising, aesthetically pleasing, and potentially informative fashion. Our pipeline is flexible and users can create their individual desired artistic expressions. We show with a survey that the visual appeal of the results vary in regard to the chosen parameter combinations. Lastly, we showcase a variety of examples that explore the design space and hope to show that a reconfiguration in itself presents a new piece of art.

Categories and Subject Descriptors (according to ACM CCS): I.3.0 [Computer Graphics]: General—; Image Processing And Computer Vision [I.4.7]: Feature Measurement—;

1. Introduction

In our everyday life we interact with multitudes of images. Our subconscious processes the visual input, and in matter of milliseconds we believe to know what we see. In order to break this routine, we present a visual experiment that offers a change of perspective on what is given. Changing ones perspective is an inherent characteristic of an artistic expression. We are inspired by the artist Ursus Wehrli, who rearranges the constituents of an image in a visually tidying up and semantically surprising fashion [Weh03]. Our pipeline deconstructs and reconfigures the constituents of an image

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automatically. This process of breaking an image apart and putting it back together again enables not only a better understanding of the image, but also shapes something entirely new in itself.

The pipeline (Figure 2) implements the mean-shift segmentation technique (Section 3.1), ten visual features for sorting in regard to the segments spatial and color value characteristics (Section 3.2.1) and two arrangement methods, one of which includes a radial and a pile-based layout (Section 3.2.2). We systematically explore the design space (Section 4) of these parameters and gain further understanding about the space with a survey (Section 5).

2. Related Work

We now briefly discuss related work for the segmentation step and the arrangement techniques of our pipeline.

Segmentation constitutes a crucial preprocessing step for a variety of applications and it is an on-going research topic in computer vision. Raut et al. [RRDR09] thoroughly review the different approaches for segmentation algorithms. Our problem requires the segmentation of color images, summarized by Cheng et al. [CJSW01], as well as an unsupervised segmentation technique for which an overview is given by Zhang et al. [ZFG08].

Arrangements of image segments can be related to our work from an artistic point of view and methodically.

Artistically, we are inspired by the art of Ursus Wehrli [Weh03], who creates image decompositions and rearrangements manually. Nonetheless, Wehrli often focuses on creating an appeal through semantic understanding, a concept which was not the focus of our work, but appears by chance in some of our results (please refer to the discussion of our results, Section 6).

Also aiming for a fragmented aesthetic appeal by transforming original image data 'piecewise', Collomosse and Hall [CH03] render from salient image features a cubist version of an input. In more recent work, Lai et al. [LR13] loosely aim for cubist appearance by segmenting an input and by simplifying the segments to constant colors, while maintaining global structures. Adding a level of abstraction, Song et al. [SPL*13] match base shapes to regions in image segmentation hierarchies. As we arrange image pieces solely controlled by segment features, we focus on an even higher level of abstraction, a goal little investigated so far in the related work.

Collage methods also implement piecewise arrangements. These techniques usually strive to fulfill certain semantic rules, such as visualizing a topic, event or story [GTZM10, ZH12]. Huang et al. [HZZ11] use thematically related image cut outs to fill any input shape, leading to an artistic appeal of their collages. Reinert et al. [RRS13] also fill a space densely with any kind of given two-dimensional graphical primitives following artistic goals. Next to collage stylizations, mosaic layouts are methodically related to our pipeline. Hausner et al. [Hau01] present the placement of mosaic tiles based on image input, following the edges flow and the coloring of the input. Dalal et al. [DKLS06] present a mosaic packing solution that integrates a novel evenness metric. Hurtut et al. [HLT*09] reproduce example element placements of stroke-based primitives. These mosaic techniques employ predefined visual primitives though, and the design space of arrangement options is limited. For our technique diverse primitive types are computed by image segmentation and we offer a range of possible arrangements.

3. Pipeline

In the following we are going to describe each component of our pipeline (Figure 2).

We use the DIN99 color space [DIN01]. It constitutes a non-linear color model, aiming for perceptual uniformity corresponding to human vision, similar to the L^*a^*b* space.

3.1. Segmentation

The quality of the segmentation of an input image highly influences the plausibility and aesthetic appeal of the reconfiguration results (Figure 5). For implementing our pipeline any segmentation algorithm could be applied. Ultimately we decided on a mean-shift method and follow the implementation from Comanicio and Meer [CM02]. After segmentation we represent the position of a segment by its center of gravity, which is the mean of all pixel positions within a segment.

In order to determine the background color, we compute two measures for each segment, the area in pixels and the number of neighboring segments. If one segment scores highest in both features, we select its mean color as background color. Otherwise, we divide the scores by the respective standard deviations and choose the segment with the highest overall quotient.

3.2. Reconfiguration of Image Constituents

The arrangement of image constituents should appear as reasonable as possible for a human observer. In this context, reasonable can be interpreted with a variety of specific semantic meanings. Ultimately we would like to control a design by how aesthetic it is, how tidy it appears and how informative it is in respect to understanding the structure and composition of the original image.

3.2.1. Control Features

Visual features refer to characteristics in the color value and spatial domain of the segments. In the spatial domain a segment can be characterized by its **size**, as number of pixels, and its **spatial standard deviation**. As the spatial standard

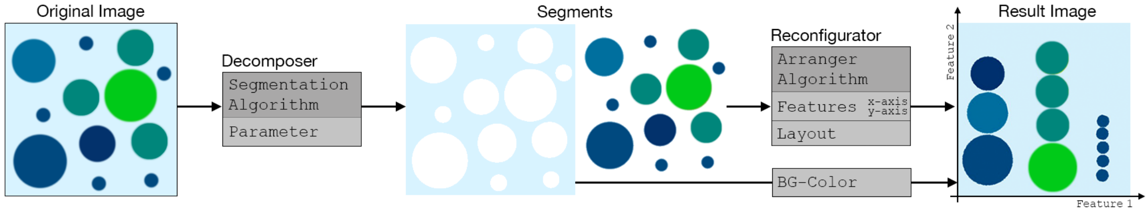


Figure 2: The decomposition and rearrangement pipeline: The user choses an image segmentation technique with its parameter settings, the arrangement method, a feature for the x- and y-axis and, depending on the arranger, an optional layout type.

deviation is dependent on the segment size, we also present the feature **compactness** as standard deviation of a segment in relation to the standard deviation of a circle with the same area, therefore representing the spatial standard deviation independently from the segment size. The **orientation** is given by the angle of the principal axis of the segment, determined by a PCA, to the x-axis of the canvas. In the color value domain we employ the **red-green** contrast a_{99}, the **yellow-blue** contrast b_{99}, the **lightness** L_{99}, **chroma** as the saturation C_{99} and **hue** as the angle h_{99} of the DIN99 model and the **color standard deviation**.

3.2.2. Arranger

Arrangements sort and group segments by positioning them on the canvas according to the control features. By defining an order and a normed distance for the segments in the feature space, we are able to project their visual appearance onto the two dimensional spatial domain and to archive a visually plausible arrangement.

Specifically, a user selects two visual features as classification criteria, which are mapped onto the x- and y-axis of a canvas. Within that space, all segments are positioned in order of the features respective specification. For the final layout all segments must be ordered and may not overlap. For making the search for a complying layout more manageable, we apply a two step process. In the first step, all segments are placed in order as initial layout, not factoring in possible overlaps. The second step then iteratively refines the layout until no segments intersect.

A refinement iteration needs to detect collisions and to push affected segments apart. For our pipeline we implement a simple constant correction force (Figure 4), which is applied in the direction of the connecting vector between the intersecting segment centers. To even further reduce the empty space between segments and to increase the appearance of tidiness, an additional rotation of the segments is possible so as to enforce parallel alignment. This is achieved through a constant force the direction of which depends on the angle between the principal axis of the segments and the x-axis of the layout.

Force-directed arrangers combine the above steps to a final layout (Figure 3 (a), (b)).

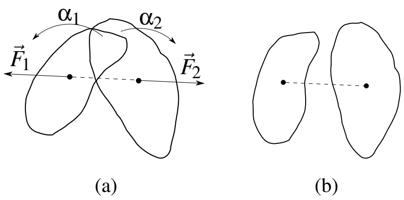


Figure 4: Detected collision in (a) and application of correction forces $\vec{F}$ for the translation of a segment and α for an optional rotation to resolve to overlap in (b).

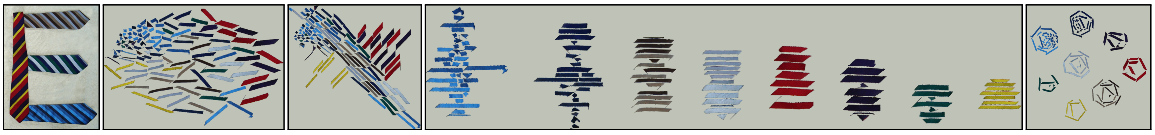
Clustered arrangers compute an additional partitioning step by clustering the segments within the two-dimensional feature space of the initial layout (Figure 3 (c), (d)). For finding the clusters in the feature space we apply again the mean-shift method. To implement the different layouts for the clusters and to ensure their compactness, additional compression forces are integrated. These forces do not take possible intersections of the segments into consideration and decrease linearly over ten iterations. Similar to the force-directed arranger, each cluster is simultaneously refined to resolve overlaps between segments with a correction force.

In the **radial layout** the compression force pushes the segments in the direction of their cluster center. The rotations of the segments are fixed to align to their cluster radii. The same strategy positions whole clusters in a radial layout.

The **pile layout** arranges all segments horizontally in the initial layout and the compression force pushes the segments to their cluster center in parallel to the x-axis. In order to position the clusters, the clusters are sorted decreasingly by their area. The pile with the largest area is placed at the bottom left corner of the canvas, with each following cluster placed with an offset in x to the right.

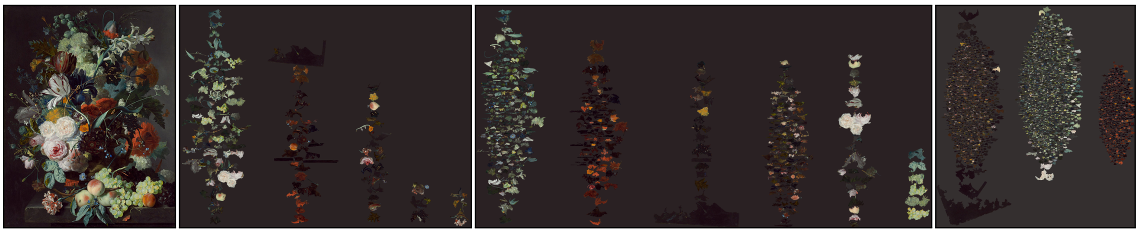
4. Parameter Space Exploration

As Section 3 illustrates, our pipeline offers a variety of control parameters that influence the visual appearance of the result. In order to support an understanding of the design space, we present several exemplary deconstructions and reconfiguration results in this section.



Original *(a)* *(b)* *(c)* *(d)*

Figure 3: Demonstration of the different arrangers and layouts: (a) and (b) employ a force-directed arrangement with the visual features size-spatial sd. (a) includes the additional rotation correction force. The clustered arranger is used with the pile layout in (c) and with a radial layout in (d), both controlled by the green red-yellow blue features. Input image: [Wri12].



Original *(a)* *(b)* *(c)*

Figure 5: Comparison of different segmentation setups from a coarse segmentation to a fine one. All reconfigurations employ the clustered arranger with the size in x and red green in y within a pile layout. The segmentation of (a) produces 124 segments in 8s, leading to an arrangement time of about 45s. (b) produces 553 segments in 10s and arranges in about 90s. (c) produces 4418 segments in 6s and arranges in about 2h. Input image: [vH15].

Segmentation settings are responsible for how recognizable the image parts remain. If we choose parameter that lead to a more chunky segmentation, image parts remain recognizable but also potentially heterogeneous. In turn, this will lead to a less tidied up impression of the reconfiguration. Also, a more rough segmentation might lead to false semantic assumptions about image parts. As shown in the third row of Figure 7, one of the segments appears to be a mouse when in fact it is just part of the bowls shadow. A finer segmentation, on the other hand, leading to more homogeneous segments overall, might produce eye-catching outliers but otherwise might appear too monotonous. Performance is also steered by the number of segments, increasing the time of the arrangement process. The refinement iterations of the segmentation and the number of segments are not know in advance. As practical performance trails, we compare in Figure 5 different segment counts and the resulting timings. We believe that performance is still improvable with some code adjustments.

Arrangement techniques lead to fundamentally different reconfiguration designs. The force-directed arranger does not regroup the feature space and creates more global and less 'tidy' but abstract and possibly more artistic appearing designs. The clustered arranger makes it easier to comprehend the image data through its hierarchical approach, making boundaries in the feature space clearly visible as clusters, as for example shown in Figure 3 (c) and (d). These boundaries are not necessarily directly sensible for a human observer or suited for deriving insights about the data of the original image. At this point we did not optimize our technique for its capabilities to visualize information.

Layout types constitute the overall large and space-filling structures within the result image (Figure 3). As an observer processes these structures as one of the first characteristics of an image, the layouts have a major visual impact. Accordingly, the results of the survey are strongly dependent on the layout type (Section 6).

Features are the control parameter the specific influence of which is most difficult to predict. Even though all visual characteristics are easy to understand, the importance of each feature is hard to judge for an observer on basis of the original image. Also, even if it is obvious which features are dominant in an image, it is not possible to anticipate how the structuring of an arranger will combine the two selected features on the canvas, especially in regard to the identified clusters of the clustered arranger. For navigating the space of feature combinations the user can explore possible reconfigurations with the help of the systems interface. Alternatively, we also offer a batch process, which generates for a segmentation setup all possible arrangers, layouts and feature combinations (see a sub-selection of the feature space in Figure 1 or all reconfigurations in the supplemental material).

5. User Study

We have conducted a user survey to understand the design space of our results better. We asked participants to identify their six most and six least favorite reconfiguration im-

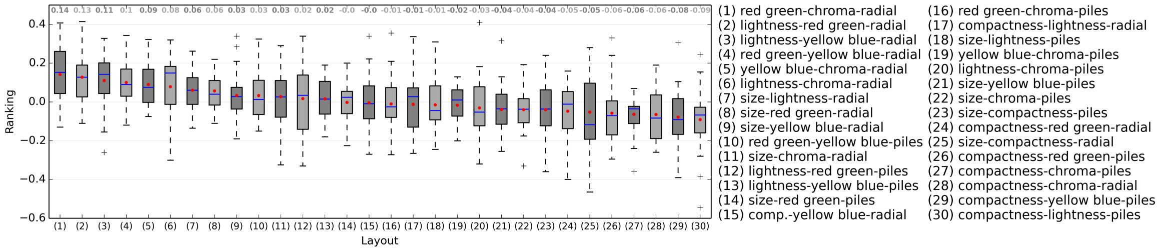


Figure 6: Boxplot for the average rankings for the different clustered layouts from the user survey. Participants selected from all options their six favorite layouts and ranked them from 0 to 1 (best) and their six least favorites with a ranking from 0 to -1 (worst). The blue line indicates the median and the red dot the mean of which the exact value is listed in the top row for each box.

ages from all unique combinations of the six features size, compactness, lightness, chroma, green red, yellow blue, with each feature combination arranged with the clustered arranger in both, radial and pile layouts. We show ten different original images and their reconfigurations to each participant. In total, we collected 28 completed surveys.

For a detailed description of the experiment design, the data and statistical analysis, please refer to the supplementals.

5.1. Results and Analysis

The survey confirmed our hypothesis that the presented layouts are differently ranked by the participants, meaning that some layouts, on an average, produce more visually pleasing reconfigurations than others.

The collected data is overall normal distributed, checked with the Shapiro Wilk test. A repeated-measures ANOVA shows a significant effect of the layout type, with $F(29,810) = 6.26$, $p < 0.001$, $\eta^2 = 0.18$ (Figure 6). Post-hoc pairwise comparisons also document significant differences ($p < 0.055$, computed with the Tukey's Honest Significance Test) between the high ranged and low ranked layouts.

The most prominent observation from the survey data is that the radial layout is strongly favored, as from the 13 layouts with a positive ranking (from 30 in total), 10 employ the radial layout. Reconfigurations with the features lightness, chroma, green red, yellow blue, therefore overall referring to color, also lead to a greater visual appeal, as all layouts with a positive ranking are controlled by at least on of the color features. The color feature red green seems to outperform the others slightly, nevertheless we believe that which color feature to chose is depended on the original image. Compactness performs significantly worse than all other features, indicating that human observers pay little attention to the quality of the shape of a segment. The poor performance of this feature must also be credited to the output size of the reconfiguration images, as small sizes make the shape of the segments hard to recognize and the arrangement appears therefore random.

6. Discussion and Future Work

We consider two **usage scenarios** for our pipeline. On the one hand, our techniques produces algorithmic art in itself, on the other hand it offers a change of perspective onto the original image data. Currently, it is up the user to set the semantic goal for the reconfiguration and to optimize the result for it. Also, optimal parameter combinations are dependent on the design of the input image. We investigate a first step towards an automatic configuration by gaining insights about human preferences and their connection to the parameter setup with a survey. Nevertheless we did not incorporate the results of the study into the pipeline. It will be worthwhile for future work to investigate an automatically predicted configuration based on the semantic goal and the type of input image. Furthermore, the pipeline has no means for a **semantic understanding** of the input image itself and to match reconfigurations accordingly. Nonetheless some lucky results mimic the content of the original image, creating especially pleasing results (see for example the middle image that looks like a fish as reconfiguration of a fish tank in Figure 1).

The applicability of our current pipeline in terms of gaining further understanding about the original input remains questionable. For controlling the reconfigurations in a degree that would enable actual **information visualization**, a user would need more direct control of the design of the reconfiguration. The envisioned system would probably be only truly meaningful with a visual analytics approach. Also, for assessing the information content of a reconfiguration, a survey should pose actual tasks for the participants to solve with the help of the reconfigurations.

Some of the factors that influence the visual appearance of the reconfiguration should have individual **control parameters**. Currently the background color of the reconfig-

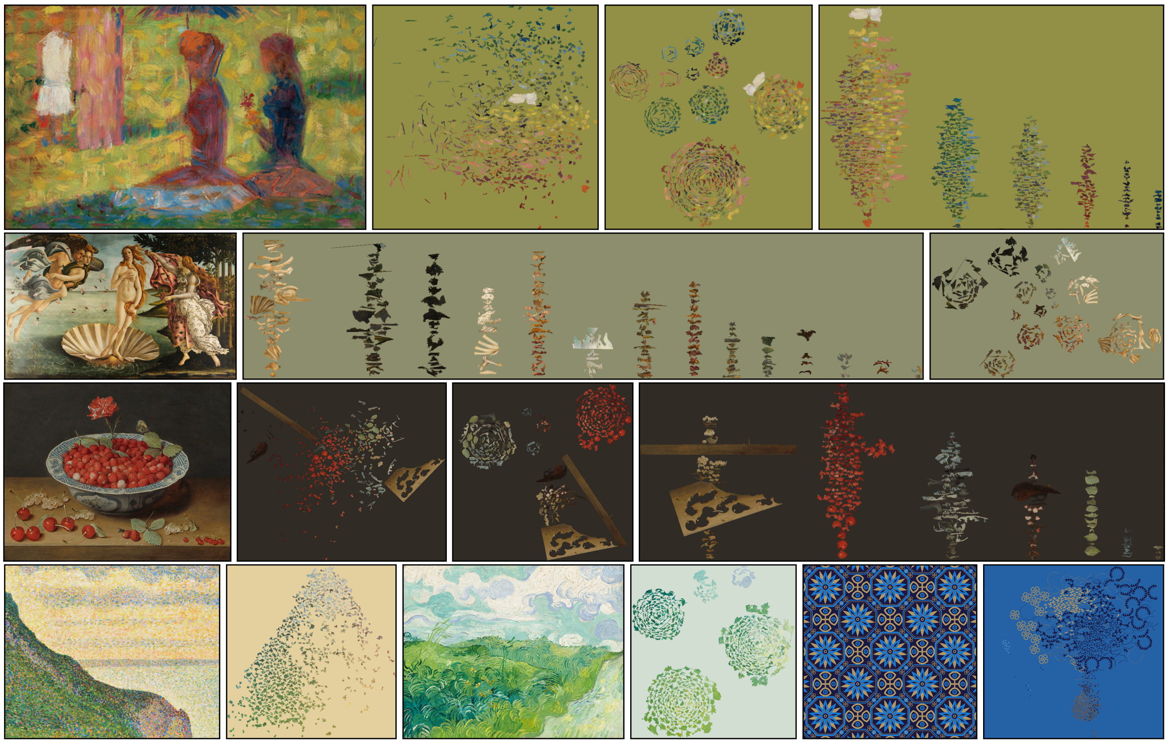


Figure 7: Exemplary reconfiguration images computed with our pipeline. Control feature from top left to bottom right in *x*-*y*: compactness-red green, compactness-hue, lightness-red green, lightness-red green, lightness-red green, lightness-color sd, red green-hue, red green-yellow blue, red green-chroma, lightness-yellow blue, red green-colorSD. Input images: [Seu88, Bot86, vH20, Seu88, vG90, Fre15]

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uration is the mean color value of the largest segment, which in turn will not be included into the arrangement. The background color has a great visual impact on the aesthetic appeal of the result as one of the first perceptual grouping steps of human vision is the figure-ground organization. Therefore, when trying to align the appearance of the reconfiguration to the original image it is important to create a similar foreground-background impression, which can not solely be based on the largest segment. For the Botticelli in the second row of Figure 7, for example, the perceived background is the sky and the background color of the reconfiguration should rather be a shade of blue than the comparatively unappealing green color it has now. It would also be worthwhile to investigate in-painting methods with the goal of applying a segment directly as background. Areas of that segment, where other segments are cut out, could be filled in a visually matching fashion.

The aspect-ratio of the images is also of importance for the visual appeal of a result and its similarity to the original. At this point, a final ratio is chosen by fitting the frame to the spacing of the segments and the new ratio doesn't necessarily match the original (Figure 7). It might be beneficial to determine the desired aspect ratio in advance and to give the user control over it. In order to further improve the global layout of the design, the 'empty' spaces between segment clusters should also be controllable, leading to more balanced results.

Additional **design options** for the arrangements of the segments are almost limitless. For example, a user could predefine shapes in which the segments should be arranged in. Also, the global structures of the original image could control the arranger.

7. Conclusion

In this work we present a technique to deconstruct an input image and to put it back together in a interesting and visually pleasing fashion. We explore the design space of our pipeline both with examples and a survey and show that with our pipeline a wide range of artistic goals are expressible. With our algorithmic art, for which we selected some more examples in Figure 7, we hope to inspire the community to shake the visual world up some more.

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