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Graph-based 3D Visualization of Color Content in Paintings

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Abstract

Visualization of the color content of a painting can help to better understand the style, compositional structure and material content. There are several ways to visualize colorimetric data from a color image. One option consists of using of 3D Virtual Reality to view colorimetric data in arbitrary orientation in a standard color space. In this paper we propose a new colorimetric visualization method. The originality of this method is that we include spatial organization of colors inside the painting. We can thus visualize information on color gradients that may appear in the painting using simple 3D primitives. We demonstrate the efficiency of our method on a colorimetrically calibrated image of an Italian Renaissance painting.

Categories and Subject Descriptors (according to ACM CCS):
I.3.6 [Computer Graphics]: Graphics data structures and data types—I.3.7 [Computer Graphics]: Color, shading, shadowing, and texture—Three-Dimensional Graphics and Realism

1. Introduction

Color content visualization of a painting helps to better understand and characterize it. Different methods have been applied to art paintings analysis in the past. These methods are either based on the visualization of the image itself, such as the luminance elevation map [CPPA08], the result of a change of illumination based on multispectral reflectance images [LAC*08] or based on the visualization of the colorimetric content of an image, such as the 3D histogram [CT03].

In order to characterize a color image it can be helpful to avoid visualization of the image itself, but to use only abstract indicators or the visualization of features. There are several ways to visualize colorimetric data from a color image. One option consists of the use of 3D Virtual Reality to view colorimetric data in arbitrary orientation in a standard color space.

The color histogram is currently the best known and widely used method of visualization of colorimetric information from an image. This, however, leads to a loss of information at different levels and to some difficulties in interpretation. Classical histograms can be viewed as $3 \times 1D$, $3 \times 2D$ or $3D$ data. $3 \times 1D$ histograms, such as the one provided by Photoshop is not characteristic of the color itself, but of the distribution of digital responses for each channel. $3 \times 2D$ histograms give only the indication of correlation between two digital channels and is still not characteristic of the color of an image. $3D$ histogram gives the indication of the frequency of occurrence of a color in the image.

The last is based on a sampling process, a quantization process and a cluster density (occurrence frequency) indicator either in an RGB digital space or in a colorimetric color space.

Different sampling processes have been used in color image processing, colorimetry or color imaging (e.g. rombohedral -equal distance from neighbors-, fibonacci -more weight on luminance-, regular squares or parallelipipedic shapes -simplicity and adaptation to hardware-). the quantization process is usually based on the occurrence frequency of a color, but several indicators and features can be taken into account (spatial arrangement, multi-level features, spreading around the cluster, contours).

While computing the 3D histograms, a regular sampling makes good sense to evaluate and visualize the frequency of occurrence of a color in a 3D space.

The weakness of this approach is multiple:

- RGB information is usually meaningless in terms of color content if not coupled with the proper transform that allows the extraction of the corresponding colorimetric coordinates.
- A 3D histogram in a colorimetric space is dependent on the metric used, the color space used (i.e. sampling of the clusters and the computation of each cluster's density), the readability of the visualization and the lack of spatial information from the image (see fig 1, the same histogram for 2 different images). Although it has been demonstrated that the 3D color histogram is a significant characteristic for color image reproduction [SM02], it does not consider the arrangement of colors inside the image, which is a critical characteristic of an image, for instance, the color of a pixel corresponding to a low frequency shift (homogeneous areas) is perceptually more important for an observer than those of a high frequency shift [VHBP00].

This article proposes a new way to visualize the colorimetric content of a painting based on color science theory and tools. We emphasize the points stated above. We concentrate on:

- Colorimetric data. The access to colorimetric data is possible since we have calibrated RGB images (i.e. it is possible to extract colorimetric content from digital data).
- Colorimetric uniformity. Each cluster has to be at an equal distance to its neighbor in a perceptual homogeneous color space, regardless of the perceptual metric used.
- The color structure of the painting. We take into account the spatio-colorimetric organization of the painting.

In order to address these problems, we propose a combination of three solutions:

- A uniform sampling of CIELAB color space conditioned by a metric. The only method proposed in the literature is to use a regular rhombohedral lattice sampling based on the computation of the euclidean metric [Wys54, Fos78, Mac78]. An equivalent sampling has been used successfully in different works [TT07, TCT07, CT09, SCB06, STCT07], however there is no work in the literature that addresses this problem for custom perceptual metrics derived from ΔE_{ab}, such as ΔE_{94}, ΔE_{CMC} or ΔE_{00} [CIE01, CIE04]. We propose a voxel based transform to generalize this uniform sampling to a non-euclidean metric. Our voxel based method generates a 3D grid where each node is equidistant from its neighbors according to a CIELAB metric (ΔE_{ab}, ΔE_{94}, ΔE_{00}, etc).
- The creation of the color palette generation through a quantization process based on the definition of different criteria (occurrence frequency, spatial frequency) that represents the spatio-colorimetric organization of paintings.
- A graph generation and its visualization of chromatic paths (arrows in the direction of a gradient, colorimetric adjacency, relationship between clusters).

We finish this paper with the application of our method to the characterization of a painting of the *Virgin and Child with Saint John the Baptist and Three Angels* by Sebastiano Mainardi.

2. Grid generation

2.1. Introduction

Our method of analysis requires us to first find a means to sample uniformly CIELAB color space while considering different metrics. We thus need to define a piecewise function that allows us to adapt a sampling structure with a metric other than the euclidean in a 3D space. Having this transform, we will be able to design a uniform sampling of CIELAB color space considering any metric.

CIELAB color space has been defined in order to relate the perceived differences between two color samples with the euclidean metric (ΔE_{ab}). This space standardized by the CIE has been obtained through the results of psycho-visual experimentations.

Because of the experimental nature of this space, the euclidean metric does not allow us to achieve an absolute perceived uniformity. To overcome this problem, CIE introduced increasingly computationaly complex metrics: ΔE_{94}, ΔE_{CMC} and ΔE_{00}. These metrics increased the quality of the estimation of the difference of color samples without modifying the space itself.

In this section, we propose to introduce a new method that permits the piecewise uniform sampling of CIELAB color space considering a given metric and a given sampling step. This transform won't be analytical, but a numerical piecewise tabulated process (a 3-Dimensional LUT).

2.2. Piecewise Transform Initialization

To yield this table, we propose to use a diffusion process on a 3-D 6-connected neighborhood from one CIELAB coordinate root. The diffusion is done from the root and follows a path based on a closest sample criterion within V-6 neighborhood. In a nutshell, it is a process that mimics the building of a cubic regular grid from a seed.

The closest sample criterion is defined as follows:

We associate a space origin coordinate with the related indices (i,j,k) to each sample of a grid that serves as a basis. i, j and k are in the direction of L*, a* and b*. Once we have defined these coordinates, all these data are ordered with their distance from the root. This process gives us the order of data processing from the closest to the further data.

At one step, one point can be adjacent to only 1, 2 or 3 other points already computed. It will be adjacent to only one point if it is on one of the axis, to two point if it is on the plane L*a*, a*b* or L*b*, to three in all other cases.

We recall that we want a 3D grid that contains in each

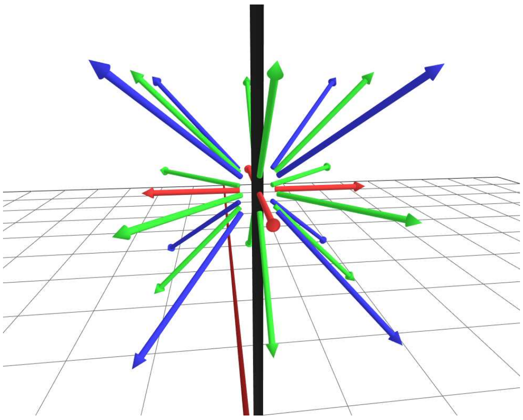

Figure 1: *Grid diffusion process*

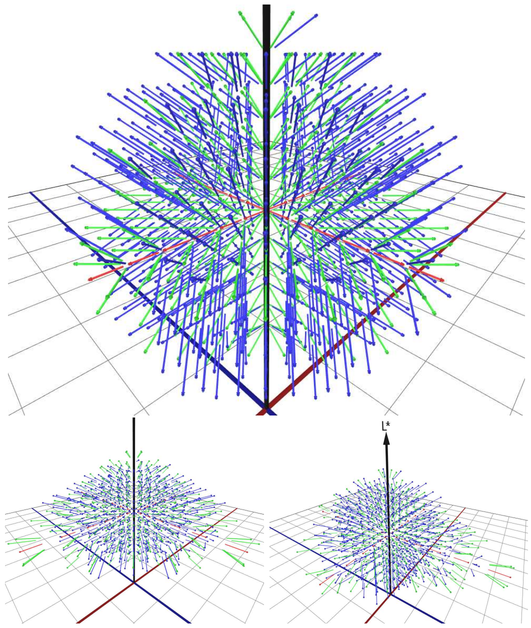

Figure 2: *Grids:* ΔE_{ab} - ΔE_{94} - ΔE_{00}

voxel the CIELAB coordinates of equidistant 6-connected neighbored data considering a given metric. The computation of each new data will be different whether it is adjacent to 1, 2 or 3 others:

1. it is adjacent to one single processed point and is on the same axis. A dichotomy process is then used.
2. it is adjacent and equidistant to two other processed points and is on the same plane. An optimization process constrained by these two constraints is then used.
3. it is adjacent and equidistant to three other processed points. The optimization process is run with only this as a constraint.

For these three cases, we use simple numerical optimization methods (tabulated methods) because some of the color difference metrics show some discontinuities, and forbid the use of analytical methods such as gradient based optimization, and leads some more complex numerical methods to local minima or makes them to diverge (i.e. ΔE_{00} [SWDC04, SWD05]).

The algorithm that build the grid needs:

- A given color difference metric on CIELAB color space
- A given sampling step within this metric
- A number of data to build within the grid, this number can be the total number of the grid data

2.3. Uniform Sampling

In the following, we explain the CIELAB space sampling algorithm, such as in previous works [SCB06, TT07]. We stay with the euclidean distance here for simplicity, but with our piecewise transform, we would be able to use any metric.

Let us introduce the following notations:

Let us call L^*_x, a^*_x, b^*_x the coordinates of a given color in the $L^*a^*b^*$ color space, and L^*_y,a^*_y,b^*_y the coordinates of a second color. The CIE ΔE^*_{ab} color distance between these two colors is the euclidean distance, such as:

$$\Delta E^*_{ab} = \sqrt{d_L^2 + d_a^2 + d_b^2} \qquad (1)$$

with $|L^*_x - L^*_y| = d_L$, $|a^*_x - a^*_y| = d_a$, $|b^*_x - b^*_y| = d_b$.

Let d_{ref} be an arbitrary distance in $L^*a^*b^*$ color space. If we consider $d_a = d_{ref}$, $d_b = 0$ and $d_L = 0$, then $\sqrt{d_L^2 + d_a^2 + d_b^2} = d_{ref}$. Likewise, if we consider $d_a = \frac{1}{2} \times d_{ref}$, $d_b = \sqrt{\frac{3}{4}} \times d_{ref}$ and $d_L = 0$, then $\sqrt{d_L^2 + d_a^2 + d_b^2} = d_{ref}$. Finally, if we consider $d_a = \frac{1}{2} \times d_{ref}$, $d_b = \frac{1}{2\sqrt{3}} \times d_{ref}$ and $d_L = \sqrt{\frac{2}{3}} \times d_{ref}$, then $\sqrt{d_L^2 + d_a^2 + d_b^2} = d_{ref}$.

Considering now the uniform color space sampling, let us give L_{min}, L_{max}, a_{min}, a_{max}, b_{min}, and b_{max} the lower and upper color values of the CIELAB color space along the L^*, a^* and b^* axis.

Considering the arrangement explained above, the 3D grid is defined such as:

- $|a^*_{i_a} - a^*_{i_{a+1}}| = d_{ref}$ the distance which separates two consecutive samples along the a^* axis, such as the distance which separates two samples along this axis is $\sqrt{\left(a^*_{i_a} - a^*_{i_{a+1}}\right)^2} = d_{ref}$.
- $|a^*_{i_a,i_b} - a^*_{i_a,i_{b+1}}| = \frac{1}{2} \times d_{ref}$ and $|b^*_{i_a,i_b} - b^*_{i_a,i_{b+1}}| = \sqrt{\frac{3}{4}} \times d_{ref}$ the distances which separate two adjacent samples along the a* and b* axis, such as the distance

which separates two samples in the a*b* plane is $\sqrt{\left(a^*_{i_a,i_b} - a^*_{i_a,i_{b+1}}\right)^2 + \left(b^*_{i_a,i_b} - b^*_{i_a,i_{b+1}}\right)^2} = d_{ref}$.

- $|a^*_{i_L,i_a,i_b} - a^*_{i_{L+1},i_a,i_b}| = \frac{1}{2} \times d_{ref}$, $|b^*_{i_L,i_a,i_b} - b^*_{i_{L+1},i_a,i_b}| = \frac{1}{2\sqrt{3}} \times d_{ref}$ and $|L^*_{i_L,i_a,i_b} - L^*_{i_{L+1},i_a,i_b}| = \sqrt{\frac{2}{3}} \times d_{ref}$ the distances which separate two adjacent samples along the a^*, b^* and L^* axis such as the distance which separates these two samples in $L^*a^*b^*$ color space is

$$\Big[\left(a^*_{i_L,i_a,i_b} - a^*_{i_{L+1},i_a,i_b}\right)^2 + \left(b^*_{i_L,i_a,i_b} - b^*_{i_{L+1},i_a,i_b}\right)^2 + \left(L^*_{i_L,i_a,i_b} - L^*_{i_{L+1},i_a,i_b}\right)^2\Big]^{\frac{1}{2}} = d_{ref} \tag{2}$$

The smaller d_{ref} is, the finer the sampling of the color space is, then the number of samples increases inversely proportionally to the distance d_{ref}.

2.4. Use of the Piecewise Transform

In the last section, we demonstrated how to generate a uniform sampling of CIELAB color space based on a closed compact lattice. This method cannot be used directly with a color difference metric other than ΔE_{ab}. To overcome this problem, we will use our piecewise morphing introduced in section 2.2. The transform is based on a 3D grid where each vertex of the voxels contains a color coordinate in CIELAB. All vertices are equi-distant considering a 6-connected neighborhood.

While using the indices space in this grid as support for our sampling (associated with the euclidean space), we can generate a list of colors that are not defined in CIELAB, but in this indices space. This 3D grid is then used for an interpolation process that allows us to map from the indices space to the CIELAB color coordinate. In this work, we used a simple trilinear interpolation, but some more complex or well adapted methods would fit as well.

The resulting sampling will not be perfectly uniform while considering the error induced by the piecewise transform and the interpolation, thus the distance between 2 adjacent points would not be exactly the same (when using a metric other than ΔE_{ab}). The study and control of the error lying on this piecewise transform will be study in a future paper.

2.5. Global Graph Generation

A quantization process allows us to build a color adjacency graph. This graph is equivalent to a Region Adjacency Graph (RAG). The Region Adjacency Graphs (RAG) provides a "spatial view" of the image. One way of representing a region adjacency graph consists of associating a vertex at each region and an edge at each pair of adjacent regions. By definition, this region adjacency graph provides a "simple-connectivity view" of the image. With Color Adjacency Graphs (CAG) we propose a different graph representation of an image. Instead of considering spatial connectivity, we model the color connectivity in an image with this kind of graph.

Figure 3: *Color calibrated image of* The Virgin and Child with Saint John the Baptist and Three Angels *by Sebastiano Mainardi, oil on panel, musée Thomas Henry. Detail used as our test sample*

This graph will contain a color defined in CIELAB at each node/vertex that has at most 12 color neighbors. In a closed compact arrangement, the neighbors will be 12 except at the border of the data cloud. When we define this sampling through the whole spectrum locus, we define what we call a global graph. The graph from an image or from a part of image will be a sub-graph of this graph.

3. Visualization

3.1. Discrete Gamut

A 3D gamut of an image will only be the intersection of the color data set, which belongs to this image, and the color space sampling data set. It can be use to compute the 3D histogram of an image.

3.1.1. Histogram

The traditional 3D histogram will consist in giving a weight to each color from the gamut that correspond to the frequency of occurrence of this color in the image. The mapping of a color to a cluster is done considering the metric we used to generate the sampling.

A way to use the histogram is to visualize the frequency of occurrence as a set of 3D primitives, which size is relative to the frequency of the colors that belong to a given cluster. In order to limit the number of primitive to display, it is better to create another structure that contains all the elements ranked by decreasing size. At this step, we have what we call an ordered cumulated histogram. It allows the visualization of the most representative colors of an image in term of occurrence. Figure 4 shows an example of this process). This figure also contains all the image colors visualized using a transparency effect.

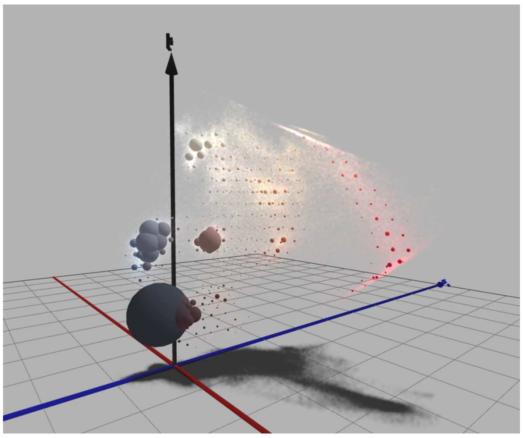

Figure 4: *Color density visualization*

3.2. Gamut Structure

Figure 5 shows another use of this graph while associated with the ordered cumulated histogram. It allows the visualization of the color gamut of the image as a 3D tubular structure. In figure 6 we can see that the colors computed during the histogram construction do not belong to the gamut structure. It is because we did not associated to each cluster the corresponding quantification color but the average color.

3.3. Spatial Information

So far, this graph structure is mainly designed for a strict color analysis. But it cannot describe the spatial organization of the colors. In order to include a spatial characterization in this structure we added information to the edges of the graph. Different spatial features can be described in theses edges. We choose for convenience to build a descriptor able to show a blending of pigments (a color gradient descriptor).

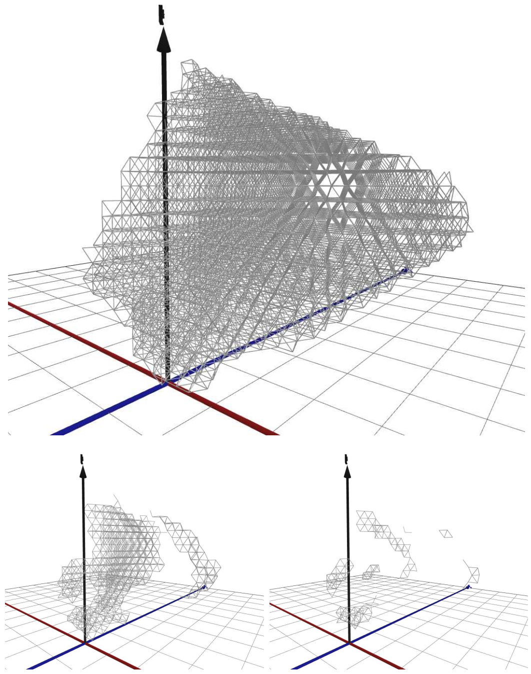

Figure 5: *Gamut of the full image - 100%, 90% and 60%*

We build this descriptor using the following method:

To every pixel from the studied image, we associate a spatial circular neighborhood of radius r. For all colors of this spatial neighborhood, we check if they are neighbors, in the colorimetric adjacency graph, with the studied color. In practice, we check if the perceived color difference between the studied color and a color in its neighborhood is below a given threshold. If this is the case, we add one to a counter associated to the corresponding edge. We process all the pixels present in the image. In the end, we obtain a measure that shows whether closed colors (considering the colorimetric adjacency graph) are spatially closed/mixed or not within the image. In Figures 7 and 8 we show the values of the edges under the shape of cylinders. The greater the size of the cylinder that links two adjacent colors, the more these colors appear in the image as a color spatial gradient, thus a spatial blend between pigments.

4. Results

Let us consider the image of the painting and the detail from Figure 3 for our example. This is a panel painting by Italian Rennaissance artist Sebastiano Mainardi from the musée Thomas Henry in Cherbourg entitled *Virgin and Child with Saint John the Baptist and Three Angels*. It was scanned in high resolution using a 13 filter multispectral camera [RSPL05]. The resulting rendering in CIELAB is colorimet-

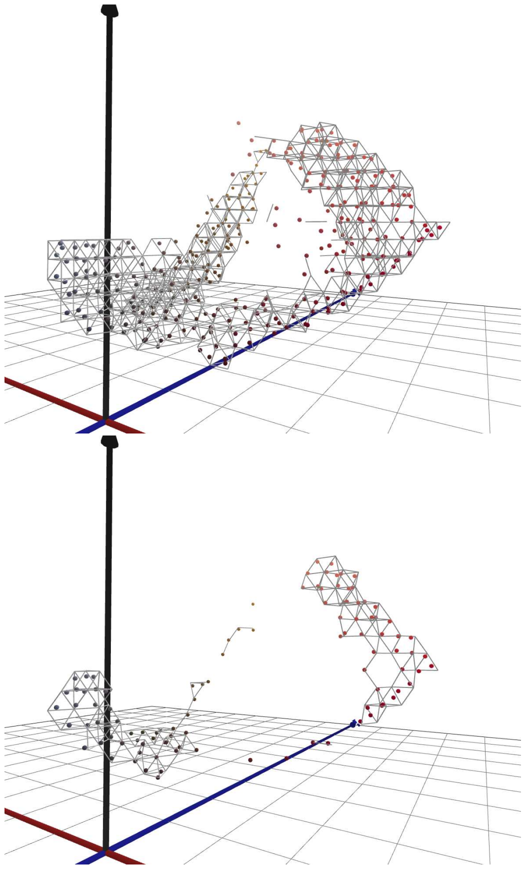

Figure 6: *Gamut of the image detail - 100% and 90% of colors*

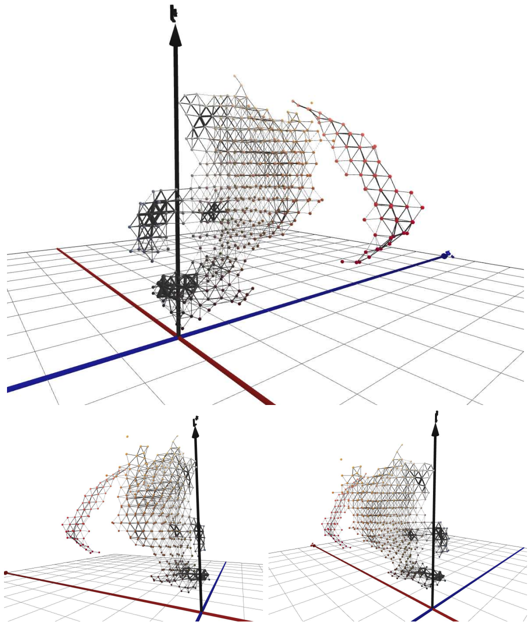

Figure 7: *Shade structure visualization of the full image*

rically highly accurate [RPSL08], which is a necessary prerequisite for performing any meaningful analysis.

With the histogram visualizations (Figures 4, 5 and 6), we can visualize in a clear, accurate and interactive way the colorimetric distribution of colors present in the painting. We can add that for the image detail, Figures 8 and 9, there are color gradients in the blue and in the red areas. Whereas for the graph from the whole image Figure 7 we note several gradients of red, blue, but also of yellow and grey.

This set of visualization methods are potentially extremely useful as an aid for painting analysis and for restoration.

5. Conclusion

The main goal of this work has been to investigate and develop a new tool to help in the study and the analysis of images of paintings. The work focused in developing something innovative for the Cultural Heritage domain using complex colorimetric analysis coupled with spatial color image vision analysis based on 3D visualization of color adjacency graphs. One of the main advances is to add new tools devoted to color spatial gradient detection.

Further work would include more gradient vision information to the visualization and to relate this information to painting techniques. In the long term, it would be possible to integrate this new data structure and its analysis into each digital report relating to paintings.

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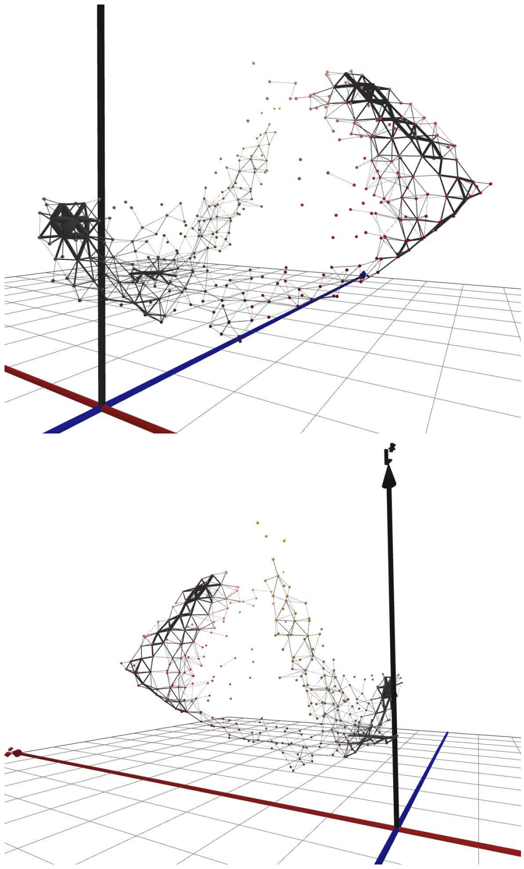

Figure 8: *Shade structure of the image detail*

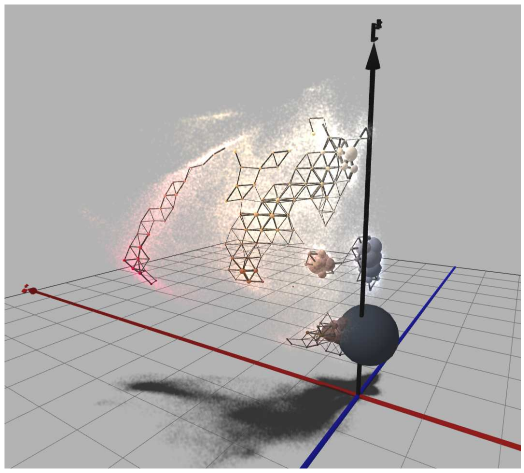

Figure 9: *Final visualization*

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