Explorative Analysis of 2D Color Maps

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ABSTRACT

Color is one of the most important visual variables in information visualization. In many cases, two-dimensional information can be color-coded based on a 2D color map. A variety of color maps as well as a number of quality criteria for the use of color have been presented. The choice of the best color map depends on the analytical task users intend to perform and the design space in choosing an appropriate 2D color map is large. In this paper, we present the ColorMap-Explorer, a visual-interactive system that helps users in selecting the most appropriate 2D color map for their particular use case. ColorMap-Explorer also provides a library of many color map implementations that have been proposed in the scientific literature. To analyze their usefulness for different tasks, ColorMap-Explorer provides use case scenarios to allow users to obtain qualitative feedback. In addition, quantitative metrics are provided on a global (i.e. per color map) and local (i.e. per point) scale. ColorMap-Explorer enables users to explore the strengths and weaknesses of existing as well as user-provided color maps to find the best fit for their task. Any color map can be exported to be reused in other visualization tools.

The code is published as open source software, so that the visualization community can use both the color map library and the ColorMap-Explorer tool. This also allows users to contribute new implementations.

Keywords

explorative analysis, color maps

1 INTRODUCTION

Color is one of the most important visual variables in information visualization. Depending on the properties of the underlying data, different types of color maps can be applied to encode data attributes visually in the most accurate way. Qualitative color maps allow for the distinction between different categories of elements. Quantitative color maps allow for an identification of similar (and dissimilar) data elements with respect to a quantitative value domain. For quantitative color maps, the most relevant representatives are either sequential (unipolar) or diverging (bipolar). In those cases where a single data variable (attribute) is encoded, a one-dimensional color ramp can be used.

For high-dimensional data, 2D color maps are used to preserve similarity of the items in a visual variable. Data items with more than two attributes are first mapped into the two-dimensional space according to some transformation or projection method. The result of these upstream techniques is a mapping in 2D that can directly be used as position information in a 2D color map.

As a result, the viewer can estimate the relative similarity of high-dimensional data by comparing colors. As such, 2D color maps are appropriate for high-dimensional data; we do not recommend the direct use of two data attributes as coordinates in the map (cf. Wainer et al. [WF80]).

A variety of different static 2D color maps has been presented in the past. The survey of Bernard et al. gives an overview [BSM*15]. The authors review quality criteria and design guidelines for color maps and depict the huge design space for the *design* and the *use* of static 2D color maps.

In order to faithfully reflect the relative pair-wise distances of the original data as closely as possible, such a 2D color map should preserve the notion of perceived similarity in terms of color. The perceived distance between colors should be linearly related to the geometric distance in both the high- and the 2-dimensional space. Another quality criterion for a color map is to exploit the given color space, aiming for a maximum number of distinguishable colors. In many cases the choice of color maps is also made with respect to colorblindness sensitivity. For example, about 8-10 percent of the male population in Europe suffer from a color vision deficiency [Alb10]. Additional requirements to color maps may be based on user-centered constraints like corporate designs. In some cases, 2D color maps may also require a certain contrast against the background color so that the visual elements can be clearly identified as such. Some other visualizations may require that text and other overlays are legible on a canvas that is drawn based on the color map.

A taxonomy of different color map design criteria is presented by Tominski et al. [TFS08]. According to the authors, meaningful color encodings strongly depend on the data, the task, the target user group, and the display device. A fourth dimension in the problem space is the large number of static 2D color maps presented in literature. Naturally, there is no color map that is perfect with respect to all requirements. To give an example, a color map can hardly be colorblind-safe and maximize color exploitation at the same time. Visualization designers need to balance a trade-off between different complementary design criteria. A premature color map decision may lead to false assumptions with respect to the underlying data properties. Consequently, choosing a 2D color map for a visualization should be done carefully.

To the best of our knowledge, a decision support system that supports the user in making such a choice has not yet been presented. We identify the following challenges:

- $\mathbf{R}_1$:Visual overview of existing color maps
- $\mathbf{R}_2$:Comparison of color maps with respect to global quantitative quality measures
- $\mathbf{R}_3$:Assessment of local properties of a color map
- $\mathbf{R}_4$:Visual analysis of the shape of a color map with respect to different color spaces.
- $\mathbf{R}_5$:Assessment of the maximum amount of discernible information that can be encoded
- $\mathbf{R}_6$:Showing the homogeneity of perceived similarity
- $\mathbf{R}_7$:Assessment of the interplay of color map with other visual variables

We present the ColorMap-Explorer, a visual-interactive decision support system for 2D color maps. The system assists visualization designers to find the best-fitting color map in this complex search space. At the moment, it contains 22 color map implementations that were discussed in the scientific literature. Visual access to these 2D color maps is provided in an overview visualization. For every color map, quantitative metrics are provided on a global (i.e. per color map) and local (i.e. per point) scale. For the comparison of multiple color maps, we provide a view utilizing the global measures. A detailed analysis of local properties is provided by several views, each shedding light from a different perspective. In particular, we allow for the detailed analysis of a) different color channels b) local perceptual linearity, and c) the shape of the area in different color spaces for every color map. In order to get a first impression of how the color map behaves in a targeted downstream visualization, several views stress the color map against other visual variables in different example scenarios. Finally, the selected color map can be exported for re-use in downstream visualization tools.

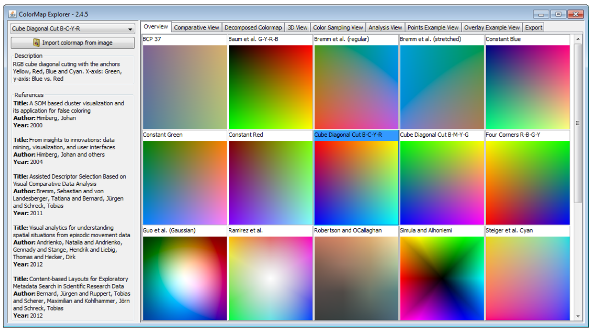

Figure 1: The main window of the ColorMap-Explorer: the config and info panel is placed on left side, the collection of views is stored in individual tabs at the right. The Overview tab enumerates all available color maps.

The workflow of the ColorMap-Explorer is as follows: starting with an overview of all color map implementations, the user can select up to three color maps which then are put in juxtaposition. This allows for direct comparison to narrow down the number of candidates with respect to the analytical task. Individual color maps are then investigated in more detail before the best fit is identified. When the decision on the best matching color map has been made, the user can save the color map as an image to disk. The user can always move backwards and forwards in this workflow pipeline as desired.

The paper is organized as follows: In Section 2, we discuss related software tools that support the user in finding colors for visualization tasks. Section 3 gives a definition of perceived color differences, before the ColorMap-Explorer is illustrated in detail in Section 4. We show some discoveries along an example application in Section 5. Conclusion and outlook are at the end of the paper in Section 6.

2 RELATED WORK

Appropriate color maps for specific tasks and specific data properties is a well discussed topic in the literature. General guidelines on selecting color maps can be found in [RO86, War88, RTB96, Rhe00]. In addition, linear color ranges (1D) for segmentation and categorical data have been discussed previously [Hea96, HB03]. For two-dimensional color maps there are few guidelines available. The study of Wainer et al. [WF80] showed that encoding of two dimensional data with two dimensional color maps is not intelligible. In contrast to this statement, Ware and Beatty [WB88] found that each additional color dimension (red, green, blue channel) is as effective as an additional spatial dimension

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in the encoding of multivariate (more than two dimensional) data. As described in [MBS*14], there is a difference between encoding single data dimensions with color and encoding (multidimensional) data relations. The first case requires a precise mapping of one data dimension to one color dimension or a one dimensional color map. The second case involves multiple dimensions for each visual object whose characteristics and relations to other objects should be revealed by color.

In [MBS*14] the authors present data-driven quality measures that are used to perceptually optimize color mapping for high-dimensional data. These measures are very effective if and only if the data set and its distribution as well as subsets (e.g., classes or clusters within the data) are known apriori and should be preserved in the color mapping. In this paper, we focus on a data-independent approach, which focuses rather on the analysis tasks and not on data properties.

In multivariate data analysis applications, two dimensional color maps have been successfully applied [RO86, Him98, SA99, SvLB10, BvLBS11, SBM*14, BSW*14] (see Figure 2 for an overview of re-implemented color maps). From this background, many two dimensional color maps have been proposed in the literature, each with different strengths and weaknesses. A recent survey has been conducted by Bernard et al. [BSM*15], enriched with a quality assessment for different tasks. Our work uses their quality metrics and provides them in an interactive manner to the user. In many aspects, our tools is similar to *PRAVDAColor*, an IBM software module that aims at supporting the user in selecting the right color map [BRT95]. Its main feature, however, is a set of perception-based rules that makes suggestions depending on task and data type.

3 PERCEIVED COLOR DISTANCE

For the rest of this paper, we will refer to a measure that indicates how similar two colors are. A reliable measure has to take the human visual system into account. In this section, we give a definition of the metric used to measure perceived color differences, also known as ΔE. Such a difference is close to zero if two colors are perceived as equal and close to 1.0 when the difference between two colors is “just noticeable” (visible by half the observers).

This definition of ΔE is based on the standardized Color Appearance Model (CAM) CIECAM02 [MFH*02]. Luo et al. have defined a ΔE for CIECAM02, based on the idea that a CAM should be a natural candidate to define a ΔE because similarity of colors should be rooted in their appearance attribute correlates [LCL06]. The authors compare appearance attribute differences to well-known color difference data sets and obtained a color difference formula and different parameterizations for the formula (see below).

They report that the predictive performance of the overarching CAM02-UCS parametrization is comparable to the specific parameterizations for small and large distances. This property is of particular importance for the evaluation of color maps, because it enables a quantification of the data-perception mismatch even when color differences are large. Previous color difference formulas were only designed and validated for small color differences.

A short definition of the ΔE is given in Equation 1; we refer to the original work of Luo et al for an exhaustive one [LCL06]. We start with CIECAM02 color appearance attribute correlates J (Lightness), M (Colorfulness), and h (Hue) and constants K_L, c_1, and c_2. The constants serve the purpose of fitting to small color distance (SCD) and/or large color distance (LCD) data, resulting in CAM02-SCD, CAM02-LCD respectively and CAM02-UCS (i.e. uniform) when fitted in combination.

$$
\begin{aligned}
J' &= \frac{(1+100c_1)J}{1+c_1J} \\
M' &= (1/c_2)ln(1+c_2M) \\
a' &= M'cos(h) \\
b' &= M'sin(h) \\
\Delta E = \Delta E_{UCS} &= \sqrt{(\Delta J'/K_L)^2 + \Delta a'^2 + \Delta b'^2}
\end{aligned}
\tag{1}
$$

Discounting for the constants, ΔE_{UCS} is an euclidean distance defined in a suitable derivate of CIECAM02. Effectively, J is being expanded by about 20%, with the coefficient c_1 actually being constant across the SCD, LCD, and UCS variants. On the other hand, the colorfulness M', is being compressed significantly, with noticeable differences between CAM02-LCD and SCD variants. According to Luo, this hints at unexplained psycho-visual differences in the chroma component when judging small and large color differences. However, most color maps do not rely on chromatic content alone to differentiate colors. The hue h remains unchanged.

In summary, ΔE is an approximation of perceived global and local color differences. Despite minor uncertainty regarding the role of the chroma component, is seems a very good assessment tool for quantifying the relation between value distance and perceived color distance inherent to color scales.

Being based on CIECAM02, ΔE_{UCS} could even account for differences in lighting conditions and surroundings, but this has not been studied. The measure is thus based on standard lighting conditions, the sRGB “typical lighting conditions” representative for office use.

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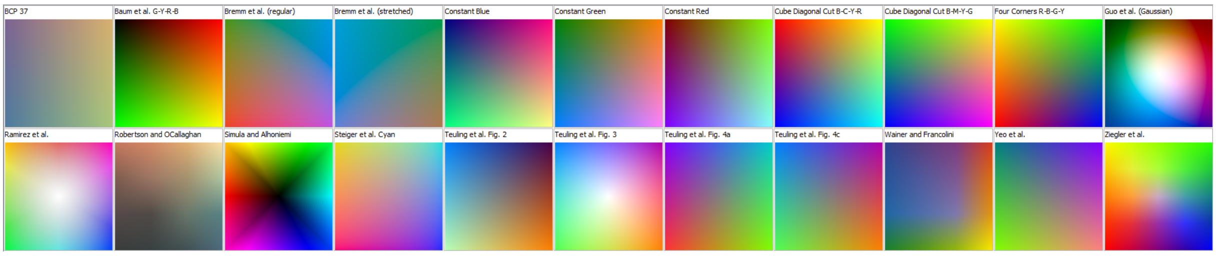

Figure 2: The initial overview lists all available color map implementations.

4 APPROACH

In this section, we present the different views of the ColorMap-Explorer along a typical workflow. The different views support the decision making process by showing individual features of the color maps. See Figure 1 for an overview screenshot of the software tool.

In total, 22 color maps mentioned in the information visualization literature have been re-implemented based on either functional description or digital images in publications. Software developers can extend the publicly available system by adding new implementations. In addition, an image-based file import enables non-experts to import custom color maps into the system. Thus, designers can easily extend the set of color maps and compare new designs with existing ones.

4.1 Overview Panel

Figure 2 shows all available color map implementations that currently exist in the ColorMap-Explorer. The Overview Panel lists all implementations as iconic images, annotated with name tags. The decision making workflow typically starts with this visualization, as this enables the analyst to gain an overview ($\mathbf{R}_1$). In this juxtaposition, the visualization designer can narrow down the set of candidates to the most relevant ones.

Criteria for this filtering step may be based on user preference such as the existence or lack of specific colors. The display device is yet another restricting aspect. For example, foreground and background colors influence the applicability for the visualization design. In addition, the analytical task may be a limiting aspect for the set of relevant color maps. A guideline for the fitness of specific color maps with respect to specific analytical tasks has been discussed by Bernard et al. [BSM*15]. Other criteria could be based on color theory or perceptual aspects such as brightness levels.

Individual color maps can be selected to get additional meta information such as scientific publications that define or reference the color map. In these publications, the user can find additional information on the construction, usage scenarios, etc. (see Figure 1, left). This information can be used to further narrow down the collection of candidates.

4.2 Comparative View

The Comparative View (see Figure 3) allows for the direct comparison of the most relevant candidates ($\mathbf{R}_2$). Six complementing quality measures indicate the fitness for a given analysis task (cf. [BSM*15]). These quality measures assess the global quality of the color map with a single value; we therefore refer to them as *global* measures. For every quality measure, score, and ranking information is provided to facilitate the comparison with all other color maps of the system. A boxplot chart displays the mean score (red line mark) and the range of 25% and 75% quantile (pink background). The 10% and 90% quantiles are indicated by a thin line (the whiskers). The color maps and their quality measures are put in juxtaposition. By that means, the visualization designer is enabled to directly compare global quality aspects of different color maps.

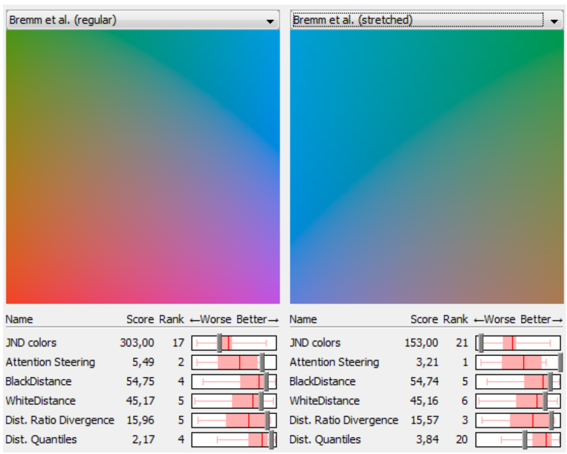

Figure 3: The Comparative View shows two selected color maps and their relative scores in different categories. This enables the user to compare scores.

As a result, the visualization designer can further reduce the number of candidates. An individual color maps can be analyzed further in the Decomposed View.

4.3 Decomposed View

The Decomposed View allows for the detailed analysis of single color maps. Two complementing aspects are considered. First, the color map is split into a set of color attributes from different color spaces ($\mathbf{R}_4$). Second, local features of every attribute can be analyzed ($\mathbf{R}_3$).

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Viewing multiple color attributes

In order to get an in-depth understanding of the properties of the color map, the map can be viewed from eight alternative perspectives. Each of them shows the same color map, but is filtered by a different color attribute.

We provide views for the red, green, and blue color components (center row in Figure 4), hue, saturation, and brightness (bottom row) as well as luma and attention steering (top row). Hue is special in that it highly depends on saturation. Without saturation, the value of hue is meaningless. Therefore, the tiles in the hue view are scaled according to its saturation. The original color map is shown in the top left panel. The first six values are directly extracted from the RGB and HSB color models.

Studies of Camgöz [CYG04] show that humans are predominantly attracted by bright and saturated colors. Attention steering effects may be harmful in several visual analysis tasks, because the analyst may be misled by striking features in the visualization that suppress less visual prominent features or patterns. Therefore, we approximate the potential of colors to attract the analyst's eye with $\sqrt{J^2+M^2}$ where J is the relative lightness and M the colorfulness. This definition accords to the findings of Camgöz et al. [CYG04]. However, it is an approximation of the attention steering effects and is yet to be evaluated. Therefore, we show both components J and M as decomposed views.

As a result, the homogeneity of a color map can be assessed. It also reveals how the color map is constructed. For example, the color map shown in Figure 4 is constructed by three diagonal color ramps in the RGB channels.

Revealing local characteristics

The spatial distribution of color in the different filtered views yields a variety of local features that can be validated. We support the user in identifying *variations* across the map with glyph-based annotations. As can been seen in Figure 4, the display of the individual views is discretized. This allows us to enrich the view with local glyphs, similar to vector field arrow grids that are well-known in the SciVis community.

We chose regular hexagons as spatial discretization, because this reveals equal spatial distances between tiles and all neighbors (in contrast to rectangular tiles). The number of tiles is automatically adjusted according to the viewport dimensions. Thus, the user can adjust the discretization level.

By default, each tile is annotated with a black arrow that indicates the perceived color distance with respect to its neighboring tiles. The length of the arrow represents the strength of the change, it points towards the strongest perceived change ($\mathbf{R}_6$). Changes are normalized across all color maps to allow for a fair comparison. The following pseudo-code illustrates the computation:

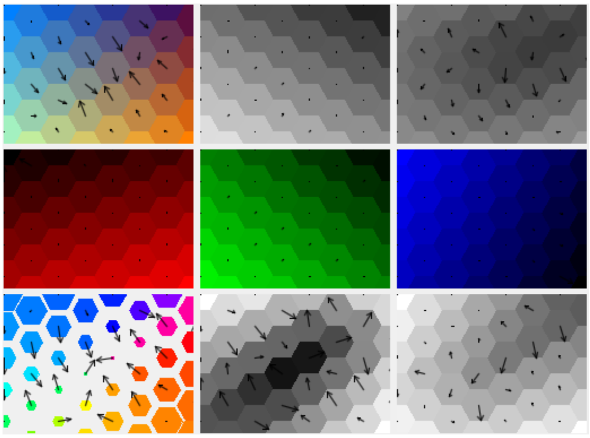

Figure 4: The color map (top left) is split into different components such as the color channels. The arrows point in the direction of the strongest perceived color change.

Algorithm 1 Compute difference arrows

```
Vector force ← [0, 0]
Color color ← tileColor(x, y)
for all Direction dir : directions(x, y) do
    Tile n ← tileModel.getNeighborFor(x, y, dir)
    Color ncolor ← tileColor(n.x, n.y)
    force += distance(color, ncolor) * dir
end for
return force
```

We compute it by averaging the color distances between the center of the tile and all neighbors in ΔE as defined in Equation 1. We avoid false assumptions caused by extrapolation by computing forces at border tiles only with a subset of tiles. As a consequence, arrows in border tiles always point along the border, never inside.

Interactive analysis of quantitative information

More detailed information on the ΔE distances of an individual tile is shown when hovering it with the mouse cursor (see Figure 5 – right). The arrow glyphs for the tile at the cursor and adjacent tiles are removed and a detailed glyph is shown instead. As a result relative color distances of a tile to the closest neighbors can be analyzed in detail. The glyph consists of six arrows, each pointing to the center of one of the neighboring tiles (i.e. they all have equal length). The stroke thickness indicates the perceived color change. Detailed quantitative information for the point in the color map at the cursor position is listed in tabular form in a separate info panel. This pane is partly depicted in Figure 5.

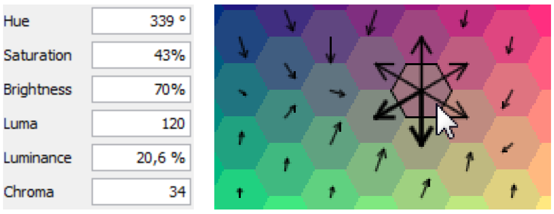

Figure 5: The detail arrow glyph shows individual differences to neighbor tiles. Quantitative information for that tile is given in the Info Panel at the left of the window.

The first two entries, X and Y, indicate the relative position of the mouse cursor on the color map in normalized coordinates. The next values represent the red, green, and blue component in the standard RGB color model that is used in many applications. The next three variables describe the color in the HSB color model, i.e. hue, saturation, and brightness. Hue is defined on a circular (connected) range from 0°-360°. Saturation and value are percentages.

CAM Lightness J is the brightness of a sample relative to the reference white. *CAM Hue* is the hue as defined in CIECAM02, which is not fundamentally different from other hue definitions, but is well-aligned to human perception because hue linearity is one of its design goals. That is, a human observer is likely to perceive the same hue when given another sample with the same CAM hue but different brightness and/or chromatic content. *Hue quadrature* is a hue measure derived from hue where the values 0, 100, 200, and 300 correspond to the psychologically meaningful hues of red, yellow, green, and blue, respectively. *CAM Chroma* is the colorfulness of a stimulus as compared to the reference white, with 0 representing neutral colors. It is designed to be independent of lighting conditions. *CAM saturation* is the colorfulness of a stimulus as a proportion of its brightness. It is designed to be independent of the perceived brightness differences observable for different hues. The CIECAM02 Brightness (Q) and colorfulness (M) have not been included due to their strong dependency to the assumed viewing conditions. The viewing conditions are chosen based on the sRGB "typical" conditions and the guidance given in the CIECAM02 technical report (CIE 159:2004).

4.4 3D View

In the 3D View, the visualization designer can assess how the shape of a single color map behaves in different color spaces ($\mathbf{R}_4$). We take advantage of the fact that the RGB, CAM02-UCS (based on CIECAM02 as detailed above), HSB, and CIELAB color space can be spanned by three parameters. We provide 3D visualizations of the shape of a color map for every color space. These four visualizations are shown side by side in the 3D View. The shape of the color maps allows for an in-depth analysis of their properties. For example, a plane in the CieLab or CieCAM02 space indicates high perceptual linearity ($\mathbf{R}_6$).

To transform the color map into the different 3D color spaces, we first sample the color map at regular grid coordinates. The color at the sampling points is then converted into the different color spaces. The Lab conversion is achieved by assuming sRGB primaries and an E reference white source as appropriate for self-luminous displays. The exact conversion routines can be found in the corresponding literature, which is comprised of CIE Publications (Lab: ISO 11664-4:2008(E) / CIE S 014-4/E:2007; CIECAM02: Technical Report 159:2004), the HSB proposal [Smi78], and the Luo et al. CAM02-UCS proposal [LCL06]. All of them have three components, and most of them can be used directly as spatial coordinates in a 3D surface plot. In order to represent the hue and saturation values of the HSB color space as spatial coordinates in 3D, we apply a transformation into polar coordinates where hue denotes the angle and saturation the radius. Consequently, the color space is a cylinder, not a cube as in the other cases.

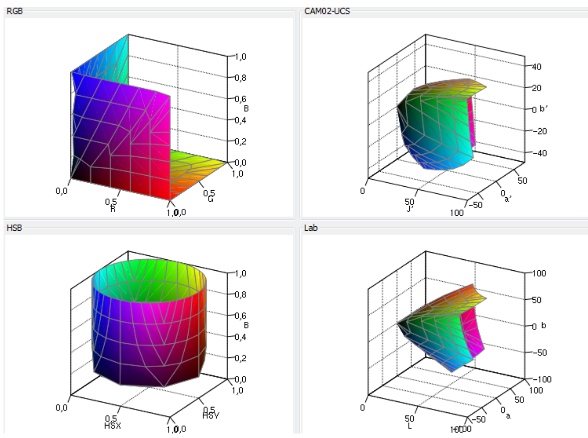

Figure 6: The 3D View of the map by Simula and Alhoniemi [SA99]: The color map is plotted in four different 3D spaces: the RGB and CIECAM02 cubes are at the top. The HSB space is actually a cylinder as the hue components defines a circle, the saturation its radius.

One of the benefits of the 3D View is that visualization designers are supported in the identification of the color space that was used for the design of the color map. As an example, many color maps are constructed as planar cuts through the RGB cube. An illustrative example based on the HSB color space is the map of Alhoniemi and Simula as shown in Figure 6. It covers the entire hue and brightness ranges at a constant saturation. This is why it appears as a cylinder in the HSB visualization. The individual 3D visualizations allow for interactive manipulation of the virtual camera. The designer can rotate the plot and adjust the axis scaling.

4.5 Color Sampling View

One of the most important quality aspects of a 2D color map is to faithfully represent spatial distances on the map with perceived color distances. This criterion is often called the perceptual linearity ($\mathbf{R}_5$). Another important aspect is the number of distinguishable colors ($\mathbf{R}_6$). The more colors a color map provides the more different information units can be encoded visually. We measure and illustrate the quality of both aspects in the Color Sampling View (see Figure 7).

Our approach first estimates the number of distinguishable colors based on the ΔE distance measure as described in Section 3. We solve an optimization problem trying to maximize the number of coordinates on the color map that fulfill the condition of a ΔE larger than a given threshold value t. The threshold is a user parameter and adjusts the minimum color distance in ΔE. A distance of $t = 1.0$ means that half of the observers are able to identify two colors as distinct. These points are depicted as white dots in Figure 7.

We compute the set of points using a circular sampling strategy: First, the center of the map is added to the result set. The algorithm then iterates on concentric circles around the center. Each of these circles is sampled in regular intervals. The number of sampling points on the circle increases with the radius of the circle increases to guarantee an equal sampling density. Once the set of points is defined, pair-wise distances are computed. For each sample point, the color distance to all points in result set is computed in ΔE. A point is added to the result set if the distance is always smaller than t. We note that is algorithm produces merely an approximation, but a valid lower bound for the number of points. Assuming that the approximation quality is similar for different maps, it also allows to compare the number of colors.

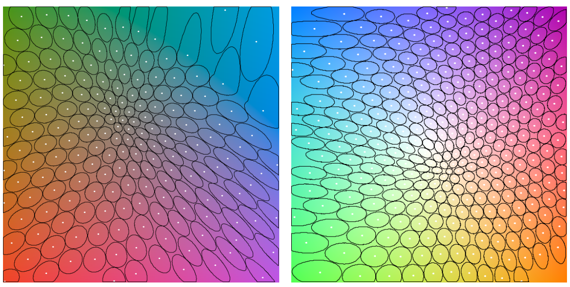

Figure 7: The Color Sampling View for the color maps of Bremm (left) and TeulingFig3 (right): white dots indicate centroids of distinguishable colors, black surrounding polygons are isolines similar to McAdam ellipses revealing information about local perceptual features.

In a second step, our approach estimates the perceptual linearity of the color map based on the regions with similar colors. Based on the set of points that define distinguishable colors, the areas with a distance of max. 1/2 t to the central point are approximated. Starting at the center, the algorithm samples along a set of straight line segments at different angles. For every line segment, we estimate the point where the threshold 1/2 t is crossed. These crossing points are connected to a iso-line polygon. The resulting polygon is similar to the MacAdam ellipse [Mac42]. Major differences are that MacAdam ellipses are defined in the xy-plane and are real ellipses based on the minimum and maximum ratio between geometric distance and perceived color distance (as measured by a human test person).

The Color Sampling View depicts the coordinates of the result set as white dots and the surrounding iso-lines as black polygons. The number of white dots indicates the number of distinguishable colors. The shape of an iso-line allows for an in-depth analysis of local perceptual features. Circular areas indicate a high local perceptual linearity, because the change of color is identical for all directions. On the contrary, distorted shapes indicate a varying local perceptual linearity. An example can be seen at the upper right of Figure 7 – left. While most shapes are rather circular, the upper right corner exhibits elliptical distortion. Individual divergences in shape can be identified easily by the user in this view.

The view also enables the visualization designer to compare different shapes. Variations in size indicate variances in the distribution of distinguishable colors. Thus, it can be seen that the perceptual linearity varies across the color map. In Figure 7, the color maps have 176 and 295 colors with a pair-wise distance of 5 ΔE. Interestingly, their distribution on the map is very different. In contrast, the map of Simula and Alhoniemi exhibits more than 600 colors.

4.6 Example Views

The usefulness of a color map for a visualization depends not only on intrinsic quality measures, but also on the usage context. Other visual environment parameters should be considered. With the example views, we support the visualization designer with test environments stressing color maps with other visual variables ($\mathbf{R}_7$).

Point Set Example

The first scenario illustrates the combination of the visual variables color (of the color map) and the position attribute. To that means, 100 equally-sized points with random colors are aligned at random positions in a point-based scatterplot. The test environment is shown in Figure 8. The visualization designer is enabled to assess the applicability of a color map for spatial object distributions. For the sake of comparability of different tests the randomization is deterministic.

Additional visual aspects of possible interest are the transparency of the colored points and the interplay of

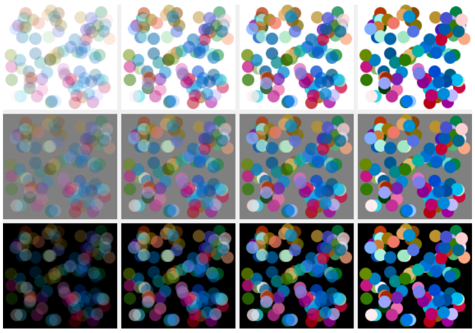

Figure 8: The Points Example View. A set of 100 points is plotted on different backgrounds with different levels of transparency. Overlapping circles are blended.

the color map with the background color. To this end, we utilize the small-multiples pattern and duplicate the test setup by means of a 4×3 juxtaposition. The 12 test setups differ in the color transparency level (25%, 50%, 75%, and 100% alpha channel) and the chosen background colors (white, gray, and black). This grid is depicted in Figure 8.

As a result, the user can immediately see whether the chosen color map has a significant distance to the background and to which extent transparency can be used.

Text Overlay View

An important requirement of many visualizations is that text must be legible. Therefore, the readability of fine visual structures (such as printed text) on colored background is illustrated in the Text Overlay View, as shown in Figure 9. Visualization designers are enabled to assess the readability of the provided text snippets in a qualitative way.

We use black, gray, and white as contrasting text colors. The text is printed at different sizes on a background that is generated from the color map. The two dynamic parameters (i.e. text color and font size) are varied in a small-multiples setup. The background of the test environments reflects the colors of the chosen color map.

Based on our experiments, the way the background is defined has a strong impact on the readability of the text. In particular, edges with sharp color contrast seem to distract the user's attention. To mitigate such effects, we use smooth (i.e. bilinear) interpolation of again pseudo-randomly selected color samples from the color map. This color is assigned to rectangles which are arranged in a two-dimensional grid in order to avoid irregular color changes. This view supports the user in comparing different environment variables in a text-based scenario.

5 USE CASE EXAMPLES

In this section, we demonstrate the usefulness of the ColorMap-Explorer. We show some of the findings that were made along an example analysis workflow.

Figure 9: The Text Overlay View. Text is printed at different sizes in different colors on space-filling background that is generated from the selected color map.

We conduct a scenario where a given color map is assumed to be ideal, be it on past experience or user preference. The visualization designer uses the ColorMap-Explorer to confirm this hypothesis. In this scenario, color should be used to encode information in a calendar-based visualization. Different results are depicted in Figure 10. The analytical task of the calendar view is mainly the comparison of individual (high-dimensional) data elements. Thus, the first important criterion is a large number of distinguishable colors to facilitate comparison tasks. The second criterion is perceptual linearity to adequately represent similarities of the data with color. Since the calendar grid is black, this color should be avoided.

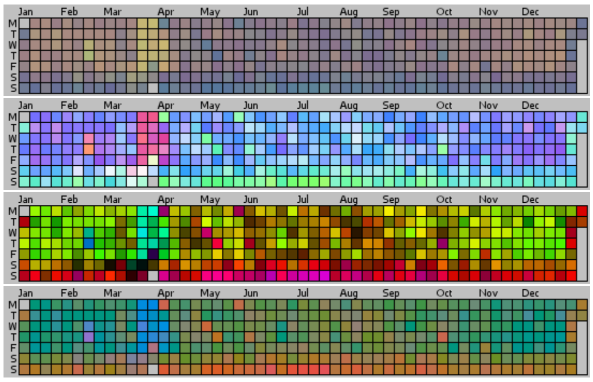

Figure 10: The calendar, rendered with different color maps. From top to bottom: BCP37, TeulingFig3, Simula and Alhoniemi, Bremm (regular).

The visualization designer uses the color map library that comes with the ColorMap-Explorer to experiment with different color maps. Some of the visualization drafts are depicted in Figure 10. While some of the visualizations are more colorful than others, it is unclear to what extend similarity of items from the original data set is preserved. She therefore starts the ColorMap-Explorer to find out which color maps are suited for this task.

After starting the tool, the overview panel comes up and the visualization designer can view all 22 color maps at a glance as shown in Figure 1 ($\mathbf{R}_1$). She realizes large discrepancies in the colorfulness of the different solutions. Her preference, Bremm et al. is about average compared to the others. Since candidate maps

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should provide high color variations, the designer excludes maps such as BCP37 (the upper colormap in Figure 10) or Robertson and OCallaghan from further analysis due to their low colorfulness.

Based on the gained overview, the designer picks the most interesting color maps including the two variations of the color map of Bremm et al. [BvLBS11]. The Comparative View in Figure 3 shows them in juxtaposition ($\mathbf{R}_2$). Although the number of colors is about average in the regular map, it is superior in the other scoring categories. Bremm et al. (regular) has a higher score than the stretched version in most categories. As a consequence, the stretched version is excluded from the candidate set.

In a next step, the visualization designer continues to the Decomposition Panel with remaining candidates for detailed inspection. In Figure 4 (Teuling Fig2. [TSS11]), the second row shows that the red, green, and blue components increase across the map, but in different directions. The colormap exploits all three RGB channels yielding a large number of distinguishable colors. However, the top-left view shows large arrow vectors along the rising diagonal. This reveals that the perceived color varies strongly leading to an inhomogeneous perceptual linearity in general ($\mathbf{R}_3\mathbf{R}_6$). As a result, the designer rejects this color map for this task.

Aiming for high color exploitation, she picks a colorful map such as Simula and Alhoniemi [SA99] from the Overview Panel. The 3D view in Figure 6 confirms that the map covers large areas in the RGB and HSB color spaces ($\mathbf{R}_4\mathbf{R}_5\mathbf{R}_6$). However, in the CieLab and CIECAM spaces the shape divergences strongly from a plane indicating a lack of perceptual linearity. As a consequence, the visualization designer concludes that the similarity of data items is not preserved well enough.

Our visualization expert returns to Bremm (regular) and opens the Color Sampling View. As can be seen in Figure 7 (left), the largest part of the map comprises small and well-shaped ellipses. However, in the top right corner an anomaly can be identified. The black outlines are unproportionally large and distorted. The color variation in these regions is very low, leading to these large areas of similar color. Despite the fact that the map is mostly homogeneous, local features in the upper right corner hamper the homogeneity of the perceptual linearity ($\mathbf{R}_3$,$\mathbf{R}_6$). In contrast, in the Teuling-Fig3. map [TSS11] (Figure 7 – right) this deficiency is less prominent. Repeating this comparison with other colormaps reveals that (and why) TeulingFig3. scores well with respect to perceptual linearity.

In Figure 8, Guo's cone-shaped color map [GGMZ05] is plotted as a randomized Point Set Example. This color map has a very high color exploitation, which makes it easy to identify differently colored circles as such. However, some of the colors are very bright and hard to differentiate on white background, in particular at higher transparency levels ($\mathbf{R}_7$). It is therefore better suited on dark backgrounds.

Looking at the example in Figure 9, the ColorMap-Explorer reveals that black text is fairly easy to read with the TeulingFig3 color map [TSS11] – independent of the font size ($\mathbf{R}_7$). On the other hand, gray and white are not ideal. One possible explanation is the similar brightness of foreground and background. Since bright text is not used in the calendar, this is not critical.

The visualization designer concludes the decision support process of the use case. From the four initial drafts only Teuling Fig3. (the second color map in Figure 10) remains. BCP37 was rejected due to the limited number of distinguishable colors. Simula and Alhoniemi has a high color exploitation, but the 3D View revealed a lack of perceptual linearity. With the Color Sampling View, Bremm (regular) was ruled out in favor of Teuling Fig3. The map has high perceptual linearity and provides a fair color exploitation. The visualization designer therefore picks this map for the calendar view.

Having started with a set of preferred color maps, the ColorMap-Explorer enabled the visualization designer to reduce the number to a single colormap. While at the beginning of the process subjective criteria prevailed, the decision support system enriched the decision making with qualitative and quantitative means.

6 DISCUSSION & OUTLOOK

In this paper, we showcased the ColorMap-Explorer, a tool for the visual exploration of 2D color maps.

It gives an overview over many color maps that have been proposed in the literature on information visualization, provides different views for an in-detail analysis of strengths and weaknesses of color maps, and supports direct comparison, both visual and quantitative (i.e based on explicit quality measures). Each color map can be exported as a high-resolution image. This enables the data scientist not only to find the best fit for a given task, but also to directly re-use the color map in other visualization software tools.

Current color maps are general purpose and independent from the data set. Similar to the optimization approach, color maps can be tailored to specific data sets in order to achieve higher overall performance. The work of Mittelstädt et al. [MBS*14] already points in that direction. The integration of such customized color maps in the explorer could help fostering that research area.

One direction for future work is the adaption of existing color maps with respect to certain quality criteria. To the best of our knowledge, it has not yet been investigated if such auto-generated color maps can be superior to manually created ones.

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