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Technical Section

Using color in visualization: A survey ☆

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ABSTRACT

Color mapping is an important technique used in visualization to build visual representations of data and information. With output devices such as computer displays providing a large number of colors, developers sometimes tend to build their visualization to be visually appealing, while forgetting the main goal of clear depiction of the underlying data.

Visualization researchers have profited from findings in adjoining areas such as human vision and psychophysics which, combined with their own experience, enabled them to establish guidelines that might help practitioners to select appropriate color scales and adjust the associated color maps, for particular applications.

This survey presents an overview on the subject of color scales by focusing on important guidelines, experimental research work and tools proposed to help non-expert users.

1. Introduction

Visualization [1] is concerned with representing, manipulating and exploring data and information graphically in such a way as to gain understanding and insight into it, i.e., mapping of data to a visual form that supports human interaction in a workspace for visual sense making [2].

Color mapping is a very important visualization technique, but the choice of the most appropriate color scale to use with a particular data set is not just a matter of choosing a colorful and visually attractive representation. Adding color which does not add additional insight to the visualization can sometimes cause confusion as users try to understand its meaning and should, therefore, be avoided [3]. So, it is particularly important to perform the right choice in order to build visualizations which depict the desired information in a clear way.

Throughout the years researchers have studied such issues and, profiting from findings in other fields such as human vision and psychophysics, managed to establish some guidelines which might help users along the process of color scale selection according, for example, to the type of data and task to be performed. Nevertheless, those guidelines are still not always used by visualization builders, and some well-documented problems are still ignored by the visualization community [4].

Extending a previous paper by the authors [5], a brief overview on the subject of color use in visualization is presented, providing information on the main concerns, findings and resulting guidelines, hopefully encouraging researchers to seek new solutions, evaluate the use of color in their visualizations and share their experience, thus contributing to a deeper knowledge on the subject.

After a short introduction to color models, this survey focuses on the desired properties for color scales and the use of color representations for univariate and multivariate data, and discusses other factors conditioning the use of color in visualization (e.g., data features, tasks to be accomplished and target audience), while mentioning the guidelines that should drive the choice of appropriate color scales and representations, as well as the advantages of applying such guidelines. Afterwards, experimental research work on the field and some tools proposed to help non-expert users are described. Finally, some conclusions regarding the existing guidelines and their usage are presented.

2. Color models

The purpose of a color model is to allow the specification of colors in a standard way. In essence, a color model is a specification of a coordinate system, and a subspace within that system, where each color is represented by a single point [6].

Several color models are described in the literature. Each of them has its own characteristics and is more or less suited to particular tasks. Therefore, before carrying on with the use of color in visualization, it is important to present a general overview on the different ways color can be represented.

In general, color models can be divided in two classes: device-dependent, when the model allows the representation of the color gamut of a particular device and the same coordinates can represent slightly different colors depending on the device features;

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and device-independent, when the model provides a representation of color using a coordinate system independent of any output device. A brief description of these two classes is presented in the following subsections.

For extended information on the subject of color models and a wider range of references the reader is forwarded to Bratkova et al. [7], which presents a new color space for computer graphics.

2.1. Device-dependent color models

In the RGB color model each color is defined by adding three primaries: red, green and blue. This is analogous to what happens in a CRT display where the phosphor has similar base chromaticities. Since there is no strict value for the chromaticity of the three primaries, the same RGB coordinates can result in slightly different colors on different output devices.

The CMY color model uses cyan, magenta and yellow as primaries, which are the complementary colors of red, green and blue, respectively. Thus, while RGB is an additive color model, i.e., by representing what is added to blackness, CMY is subtractive, representing what is subtracted to white light. This color model is usually used in color printers. In many situations black is added to this model, in order to allow a better representation of darker colors, and such color model is identified as CMYK.

Although the RGB color model is based on the way color is represented in a CRT monitor (and thus sometimes called, along with the CMY color model, hardware-oriented [8]), it does not relate well with the way color is intuitively perceived. Thus, as an alternative, two additional (user-oriented) color models have been proposed: HSV (hue, saturation and value) and HSL (hue, saturation and lightness). These are based on the intuitive appeal of a painter's tint, shade, and tone.

2.2. Device-independent color models

The three primaries red, green and blue cannot be used to represent all visible colors (at least using only positive values). In 1931 the *Commission Internationale de l'Éclairage* (CIE) [9] defined a new color model, CIE XYZ to avoid this problem [8]. Three new standard primaries (X, Y and Z) were defined, thus allowing a specification of all visible colors using only positive values.

Two additional color models have been defined, derived from CIE XYZ, which are perceptually uniform: CIE LUV and CIE LAB. In a perceptually uniform color model the euclidean distance between a pair of colors in the color space is directly connected with their perceptual distance, i.e., if two pairs of colors have the same euclidean distance among them, their perceptual distance is the same. The first perceptually uniform color system, which was also an influence to CIE LAB, was the Munsell color system [10] which is still in use.

3. Desired properties for color scales

Given a sequence of numerical values $\{v_1 \leq v_2, \ldots \leq v_N\}$ represented by colors $\{\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_N\}$, respectively, it is possible to identify the following desirable properties [11,12] for a color scale:

Order—The colors chosen to represent the numerical values must be perceived as having the same order as them, i.e., if the values are ordered, the colors chosen to represent them must also seem ordered. An example can be the representation of a temperature scale by using the notions of *cold* and *warm* colors and their proportional mixtures in order to obtain a scale from cold to hot temperatures.

It is important to note the special case of nominal data [13]: objects should be distinguishably different but, since they are not ordered, there should be no perceptual ordering in the representation.

Uniformity and representative distance—The color representation of two values should convey the distance between them, and colors representing values which equally differ from each other should also seem equally different. Beyond that, it is required that clearly separated values must be represented by distinguishable colors, and that close values must be represented by colors perceived to be closer. This is what Trumbo [12] calls the *separation principle*.

When representing flow information, for example, complementary colors can be used to represent flows in opposite directions and similar colors (with slight differences) to represent flows in the same direction. Levkowitz et al. [11] identify analogous principles proposed by Pizer et al. [14] (*associability*) and Robertson et al. [15] (*separation*).

Boundaries—If there are no boundaries on the represented numerical data the color scale should not create this effect, i.e., the color scale must be able to represent continuous scales.

Rows and columns principle—This is one of the principles proposed by Trumbo [12] which applies only to bivariate information. It states that if it is important to preserve univariate information, then the display parameters must not obscure one another, i.e., rows or columns having a constant value of one variable must have constant hue, saturation, or brightness. For example, using two display primaries (e.g., red and green) goes against this principle.

Diagonal principle—The second principle proposed by Trumbo which only applies to bivariate information states that if the detection of positive association of variables is a goal, the displayed colors must be easily identified as belonging to one of the three classes: the ones near the minor diagonal, the ones above it, and the ones below. This could be accomplished with the major diagonal made up of greys, elements of maximum saturation, or constant hue. A hue and lightness scheme violates the diagonal principle [13].

4. Univariate representations

When using a color scale to represent univariate data, each color represents a single scalar value. It can be a continuous color scale, if color varies along the scale in such a way that adjacent colors are similar to one another, or a discontinuous color scale if that does not happen.

In what follows some examples of continuous color scales are presented (according to a survey by Rheingans [16]). Additional examples can be found in [17].

4.1. Color model components

Grey scale—This color scale (see Fig. 1) maps scalars to brightness. It consists in a variation from black to white, with black representing, in general, the lowest value and white the highest.

While this color scale presents some advantages, such as an easy to perceive ordering (the different and increasing brightness levels), it suffers from the fact that it displays a low contrast between the different colors, which limits its use in quantitative tasks.

Rainbow scale—This is one of the most popular color scales used in the visualization literature [4]. It consists in a color path along the different colors of the rainbow, built by varying hue while keeping saturation and contrast at fixed values. For example, in HSV, it consists in a complete rotation around the value (V) axis.

Regardless of its popularity, this color scale presents several problems [18]. For example, to some users it might not present an intuitive ordering unless they are familiar with the color progression (light spectrum). The position occupied by some of the colors might

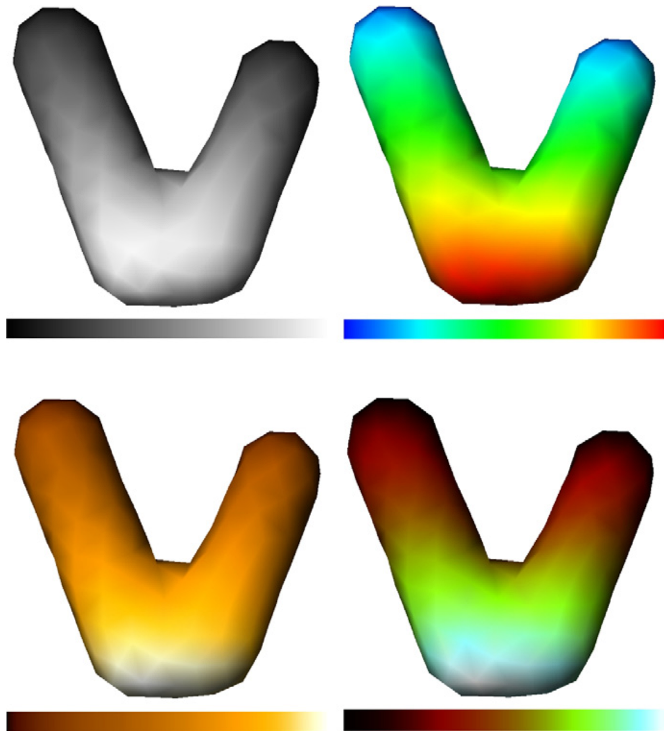

Fig. 1. From left to right and top to bottom: greyscale, rainbow, heated-object, and linearized optimal color scales applied to a data set. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

also lead to problems. Yellow is present half way through the color scale. This means that if one is interested in depicting extreme values the middle values might interfere, since yellow has an highlighting effect being perceived as brighter than the other colors. Another important aspect whenever using yellow in a visualization is that it has the smallest number of perceived saturation steps [19]. Therefore, users find it harder to distinguish small saturation variations for yellow than, for example, for blue.

Another issue might be the fact that this color scale goes from red to violet. Since these colors are quite similar, both extremes will get visually close. To avoid this problem the color scale is usually cut at blue (as seen in Fig. 1).

4.2. Redundant color scales

Using multiple display parameters to represent data may have several advantages [16]. First, one can draw benefits from the characteristics of various display parameters in conveying different kinds of information: while brightness is more effective conveying shape, hue is better in providing distinguishable display levels.

This kind of redundancy might also help in dealing with situations where one of the parameters becomes ambiguous (e.g., due to a visual deficiency) and is compensated by the others.

Finally, using redundancy might also allow a better distinction between values by reinforcing their visual differences.

Ware [20] has studied redundant color scales and proved their utility by performing several empirical studies, which led to a suggestion that a color scale varying in both luminance and hue can be used to accurately represent both metric and surface properties. Some examples of such scales are:

- *Redundant model components*—A straightforward redundant scale can be built by mapping data values to both hue and brightness. That kind of color scale has the advantage of being suitable for use by someone with dichromatic color deficiency.
- *Heated-object scale*—This scale represents a compromise between the grey scale and the rainbow scale. It goes from black to white, passing through orange and yellow. This color scale has a stronger perceived natural ordering than the rainbow scale, since it has a monotonic increase in brightness (see Fig. 1).
- *Linearized optimal color scale*—This color scale was introduced by Levkowitz et al. [11] to describe a scale which maximizes the number of JNDs (just noticeable differences) while preserving a natural order (see Fig. 1).

4.3. Double-ended color scales

Such color scales are created by joining two monotonically increasing scales at a common end point. For example, one can join a scale from grey to red and a scale from grey to blue, building a scale from red to grey to blue. With such color scales it is possible to visually represent high, low and middle values clearly, since they exhibit three distinct groups of colors.

A recent work by Moreland [21] discusses the creation and use of double-ended color scales, for example, as an alternative to the rainbow color scale.

5. Multivariate representations

It is common that a single visualization requires the depiction of multivariate data. Multivariate color scales, and color blending and weaving are presented in what follows, as alternatives for representing multivariate data.

5.1. Multivariate color scales

In a multivariate color scale two or more data variables are mapped to a single color representing them all. This is the same principle as the one used with redundant scales, but now each display parameter is related with a different variable.

Working with the RGB color model, it is possible to map a variable into each one of its components, thus creating a multivariate color scale. For example, Landsat "false color" images are commonly produced by representing three multispectral scanner bands with levels of red, green and blue [22]. Therefore, if the represented bands are highly correlated, the image will be composed of shades of grey, since the three components will have close values. This scheme has the advantage that the extremes of the variable range (black, red, green, blue) are easily detectable.

An analogous scheme can be obtained using, for example, the HSL color model. For more details on the possible approaches see [16].

A problem occurs when one needs to decompose the shown colors in their components. How can we detect similarities between areas that have the same value for two components but differ on the third?

5.2. Color blending and weaving

Another approach for multivariate representations using color can be to use different color scales for each variable and then blend the results. This approach might also pose a difficulty in identifying individual values for each variable. Urness et al. [23] introduced a technique named color weaving, applied to flow visualization, which consists in coloring the line integral convolution using side-by-side streamlines of the different colors which need to be represented in a region. Fig. 2 shows an example of this technique compared with color blending.

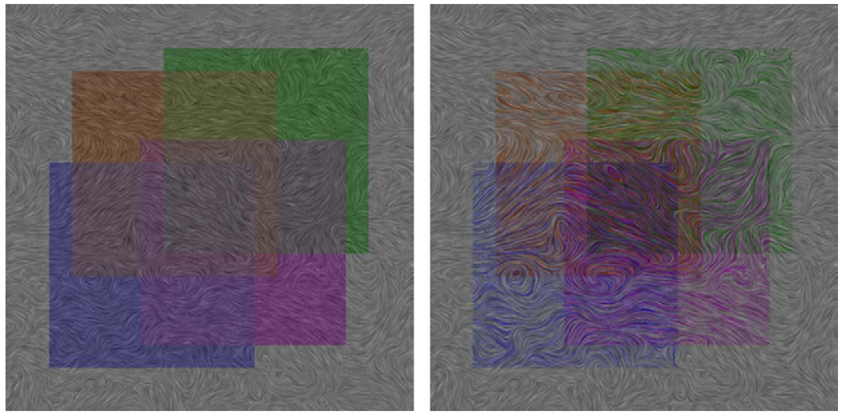

Fig. 2. Color blending (left) and color weaving (right). Reproduced with permission from [23]. © 2003 IEEE. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

A study by Hagh-Shenas et al. [24] compares user performance when analyzing information represented on maps using color weaving and the more traditional color blending (consisting in a linear combination of all the colors which need to overlap in a region). Color weaving is performed by representing the individual colors side-by-side, in a high frequency texture which fills the region. Results show that users perform better when color weaving is used, particularly when more than two colors are being represented. Nevertheless, performance decreases for more than four colors. A possible alternative to extend this limit might be a technique earlier presented by Shenas et al. [25] which uses color and texture. Further work regarding color weaving can be found, for example, in Luboschik et al. [26] who present color weaving applied to scatter plots.

Recently, Wang et al. [19] proposed a framework which uses a set of guidelines to support choosing the proper colors for a visualization when color blending is used, e.g., to depict objects that partially overlap and where perceiving the stacking order (which object is in front/back) is important.

Whenever two semi-transparent objects overlap, it is easier to perceive which one is in front if their colors have opposite hues (e.g., red and blue) than closer hues (e.g., red and green), since the overlapping region in the first case will exhibit a hue closer to the object which is in front (or at least neutral) while, in the latter case, the overlapping region will present a new (shifted) hue. In situations where more than two objects overlap, a set of hues must be chosen as to avoid any hues which can be generated by mixing other hues in the set: a general rule is to choose opposing hues for the two most important objects and then neutral colors for all others. Furthermore, for situations where multiple objects overlap, using different opacities might also help users to perceive object order by decreasing object opacity from front to back. Saturation might also play an important role in avoiding drastic hue changes in overlapping regions, or in object order perception, by increasing saturation for front objects and decreasing it for back objects. Finally, Wang et al. also found that cold colors (e.g., blue and green) tended to be perceived as being in front, even if their opacity was lower than remaining objects. The opposite was true for warm colors (e.g., red and yellow). This was an unexpected result since it is the opposite effect which is, in general, observed (due to chromostereopsis [3]). For several examples the reader is forwarded to Wang et al. [19].

Chuang et al. [27] extended Wang et al. [19] work. Their main improvement is that they manage to perform blending by preserving the hues of each object and avoiding the appearance of new (shifted) hues, with no need for an initial careful selection of opposing hues. They also introduce the concept of dominant color, i.e., the color that has more impact on the final image as opposed to Wang et al. which always consider the foremost hue to be the most important.

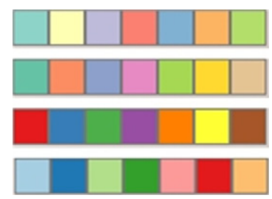

Fig. 3. Quantitative scales available in ColorBrewer 2.0 [29] suitable for nominal data representation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

6. Visualization characteristics and color scale selection

The color scales and methods used to build a visualization do not depend only on the number of data variables involved. Several factors such as the characteristics of the data, the tasks which need to be accomplished or the target audience are important enough to be considered.

6.1. Data types

When designing a visualization (i.e., picking a color scale) care must be taken to ensure that the most striking features of the image reflect the most important features of the data. If a representation catches the user's attention with unimportant features of the data, more interesting features might be missed [16]. Bright colors, sharp boundaries, or high saturation areas will most likely catch the user's attention. Thus, it is important to consider the data that will be represented and their type, and know what is more important: for example, to call attention to middle values or to positive/negative deviations from a zero (threshold).

It is possible to distinguish between four data types [28]:

Nominal data—For nominal data no mathematical operations are possible, since the value assigned to a particular measurement represents a name. An example is the categorization of different lung diseases with numerical labels 1, 2, 3 and 4: no mathematical operation is meaningful on these data. Here, numbers are identifiers. As noted above, the representation used for these kinds of data should not implicitly order it. A bad choice would be to use a grey scale since users intuitively perceive an order from dark to bright or vice-versa [4].

Fig. 3 shows several segmented color scales provided by ColorBrewer [29] (part of its qualitative color scales set) which could be used to represent nominal data.

The number of colors used to represent nominal data should be restricted to seven or less [3]. This guideline is based on two constraints: users ability to discriminate between colors and their ability to remember the meaning of each color while looking into the visualization.

Ordinal data—With ordinal data, values are assigned to measurements (for example), but no assumption is made about the spacing in-between such measurements, i.e., there can exist a numbering of 1, 2, 3 and 4 but the distance between elements 1 and 2 cannot be assumed to be equal to the distance between 3 and 4. Ordinal data are inherently discrete [30]. The used representation should allow discrimination between objects and the perception of their relative order.

The quite common rainbow scale, for example, would not be a good idea to represent ordinal data. Even though it can be said that it is an ordered scale, if we consider wavelengths, it is not perceptually ordered [31,32,4]. Fig. 4 shows several examples of suitable segmented scales provided by ColorBrewer [29] (part of the sequential color scales set).

Interval data—For interval data, the numerically equal distances between values are assumed to be actually equal. These kinds of data are commonly a (experimental) measure such as temperature, etc. The used representation should account for this: equal steps in data values should correspond to equally perceived magnitude in the representation. A perceptually uniform color space can be used to help choosing the appropriate colors.

Fig. 4. Sequential scales available in ColorBrewer 2.0 [29] suitable for ordinal data representation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Ratio data—On ratio data, ratios between values are assumed to be equal and values increase/decrease monotonically about a true zero or threshold. This feature should be preserved in the representation. An example is absolute temperature measured using the Kelvin scale.

If the ratio data have a relevant zero crossing, it can be preserved by using a double-ended color scale with a transition at zero. If the data are to be represented by a segmented color scale, then it is probably a good idea to have an even number of steps (with a transition at the zero level).

6.2. Spatial frequency

An important issue to consider when choosing a color scale is human spatial vision. The luminance and saturation mechanisms in human vision play an important role in spatial sensitivity, but they have different characteristics. The human visual system accurately processes high-resolution images, or data which varies rapidly over an area, if that spatial variation is represented as a variation in luminance, i.e., the luminance channels are responsible for processing high spatial frequency information. This means that, when representing data with a high spatial frequency, it is a good idea to use a color scale which provides a strong luminance variation across the data range [33]. On the other hand, the saturation mechanisms in human vision are more sensitive to low spatial frequency variations.

Such kind of effects are illustrated in Fig. 5. On the top row, a frequency modulated grating beginning at one cycle per image and increasing in spatial frequency is presented (the corresponding waveform is presented on the first column). The variation is represented using a saturation varying color scale (in the center) and a luminance varying color scale (on the right). Notice how the saturation-variation color scale makes the sinusoidal variation more visible, at the low frequency end of the spectrum, than the luminance varying color scale. On the bottom row, the opposite happens: with the saturation varying color scale (in the center) you can only observe the first few cycles of the frequency modulated grating, observing twice as many when using the luminance varying color scale (on the right).

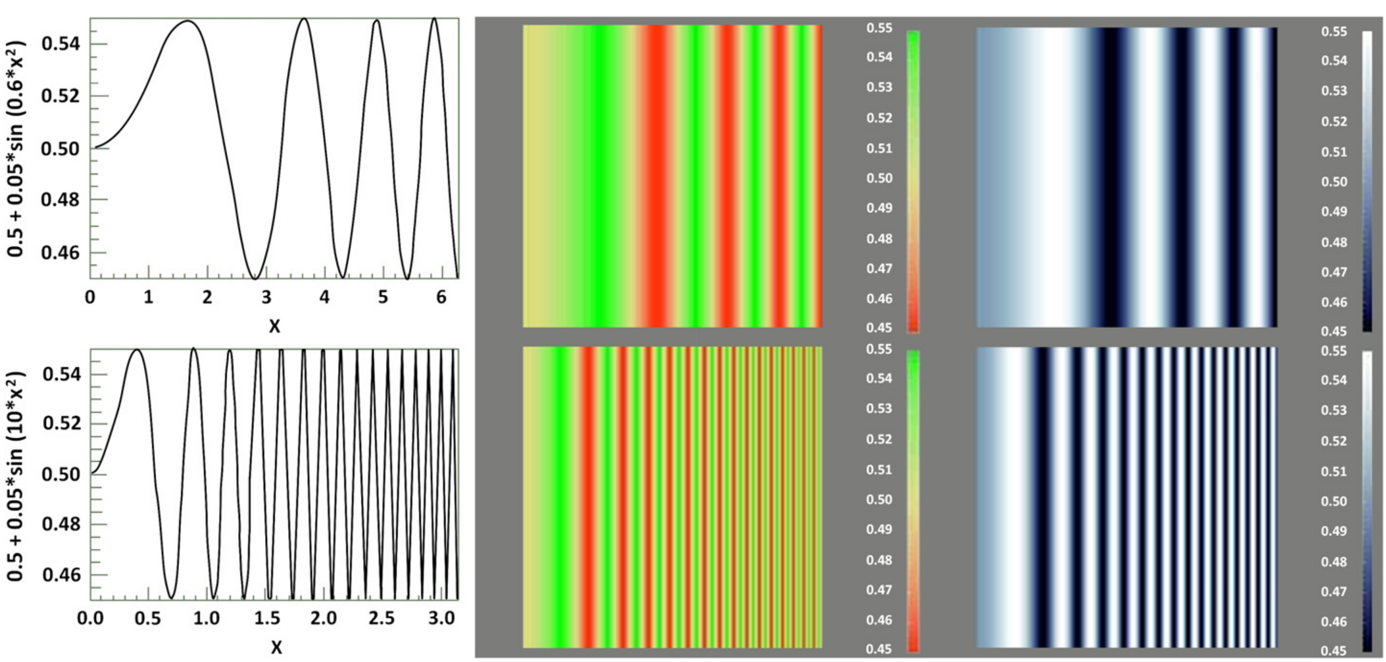

Fig. 5. Two frequency modulated gratings represented using a saturation varying color scale (center) and a luminance varying color scale (right). Reproduced with permission from [30]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Looking, for example, at interval and ratio data, both luminance and saturation varying color scales can produce the effect of having equal steps in data to be represented by equal perceived steps on the color scale, but the first will most certainly be more adequate to high spatial frequency data variations, while the second will be more suited for low spatial frequency variations.

6.3. Task/goals

The goal of a particular visualization is an important issue when choosing a color scale. Tasks which require the judgment of metric quantities in the data tend to be better accomplished with color scales which do not vary monotonically in the opponent color channels (brightness, red–green, yellow–blue). On the other hand, tasks involving qualitative judgments about value distribution shape are better served with color scales varying systematically in brightness, allowing our visual system to employ familiar shape-from-shading mechanisms [16].

In situations where the perceived size of an object is important, care must be taken in how the object is colored. An early study by Tedford et al. [34] found a significant color-size effect leading to a conclusion that warm colors such as red, orange and yellow appear larger than cool colors like green.

In another study, by Cleveland et al. [35], users were asked to judge, on a map with equal colored areas in red and green, which one was the largest: the average observers considered the red areas were larger. The obtained results suggest also that the color–size effect grows stronger for very saturated colors, which indicates that these colors might not be the better choice for tasks where the user is expected to make judgments about size.

Considering the kind of task to perform, the color scale can be designed accordingly [13].

For example, regarding segmentation tasks, some of the rules used to create isomorphic color scales for ratio and interval data are also useful for creating maps for segmented data. In high spacial frequency data, luminance can be used to convey monotonicity; in low spacial frequency data monotonicity can be conveyed through the saturation component.

When creating a segmented color scale, it is necessary that the segments be discriminable from one another. This will limit the number of steps which can be represented. Bergman et al. [33] state that a higher number of steps can be effectively discriminated for low spatial frequency data than for high spatial frequency.

In Fig. 6, on the left side, a five-level segmented color scale is used and, on the right side, a ten-level segmented color scale is used. They are applied to low spatial frequency data (top) and high spatial frequency data (bottom). For the low spatial frequency data (top row), having additional levels provides additional information. For this particular case, additional features of the earth's magnetic field are revealed (notice the southern hemisphere). On the contrary, on the bottom row, showing high spatial frequency cloud fraction observations, additional features are not revealed by increasing the number of color scale steps.

Another notable example concerns highlight tasks. The principles which should guide the selection of a color scale for highlighting particular features in the data can be found, for example, in Julesz [36]. Using those principles, it is possible to design color scales which draw attention to a particular range in the data. When dealing with high spatial frequency data, for example, a possible approach can be that of using varying saturation to represent the information (maintaining constant luminance), while modifying the hue in the regions needing to be highlighted.

The work of D'Zmura [37] and later work by Bauer et al. [38,39] have treated the topic of linear separability, which can also help in highlighting tasks. When a target has a color which can be separated from all other background colors with a single straight line in color space, it will be easier to detect, i.e., its perceived difference from all others will be clearer.

Another important aspect regarding hue is that similar hues are perceived as part of the same group [19] which leads to, for example, separate regions on the display having similar hues being perceived as having a connection. This is useful if the goal of the visualization is to detect groups within the global data. The

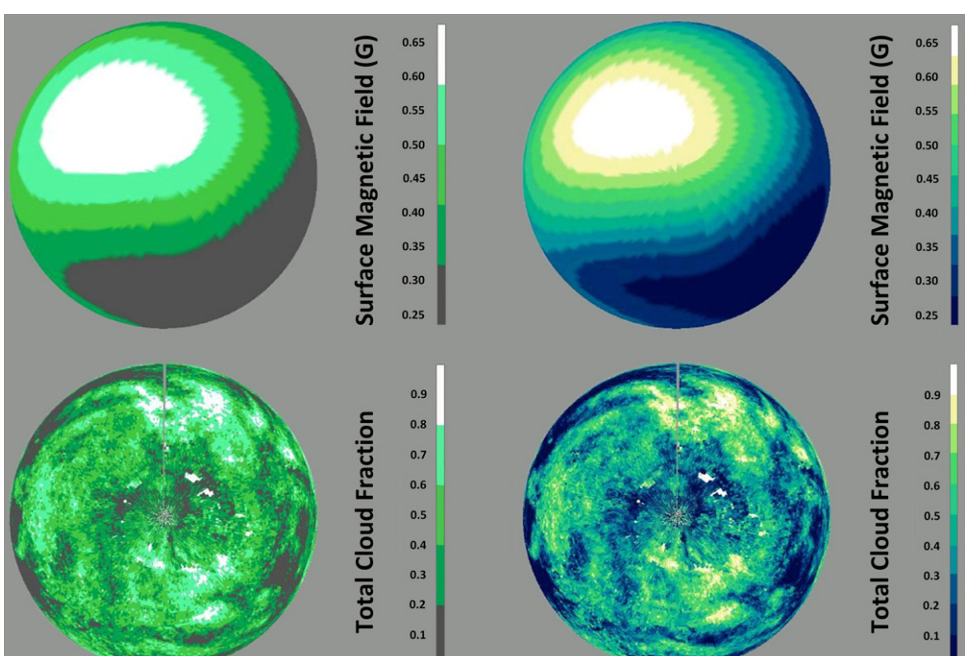

Fig. 6. Segmented color scales applied to low (top row) and high (bottom row) spatial frequency data. Reproduced with permission from [13]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

different groups can be represented by different (more distant) hues. Nevertheless, it should be noted that color should probably be reserved for the most important groups (while using other graphical dimensions as shape and size for other groupings) or this advantage will be reduced [40].

Recently, Tominsky et al. [41], based on a task model proposed by Andrienko et al. [42], have presented several strategies for adapting the color mapping to specific tasks such as segmentation, localization (highlight) and comparison. For lookup tasks, for example, they use two techniques, histogram equalization and box-whisker plot adaptation, in order to build a color mapping which assigns a higher number of distinguishable colors to the value ranges where more data values are concentrated.

6.4. Visualization type

It is important to consider the whole visualization during the process of color scale design for the individual elements. For example, 3D visualizations have different constraints than those imposed by 2D visualizations. A good example of the problems that can occur is related with shading: if users use shading cues to judge the 3D shape of a representation object (e.g., an isosurface); a brightness varying color scale might interfere with the brightness values resulting from the shading calculations. Nonetheless, a brightness varying scale may be used in planar objects on a 3D scene.

Due to the way human vision focuses on the different colors [3] in a 2D visualization a red region is perceived as closer to the user than a blue region thus creating a depth effect. Therefore, adjacent regions of strong blue and red should be avoided to prevent this effect.

Another issue might arise from the requirement of displaying multiple variables in the same visualization. The used color scales should not generally overlap, with the representation for each variable interfering with the others as little as possible. For this purpose, the weaving techniques reviewed above might provide a solution.

When representing multivariate data, motion can also play an important role as it provides an additional dimension.

Even though color is commonly considered irrelevant in the perception of object movement, Weiskopf [43] proposes a set of five guidelines, supported by a set of psychophysical results described in the literature, which concern the use of color to better convey motion in visualization.

Those guidelines focus on improving motion perception and the discrimination of motion direction, on using moving color patterns to highlight and visually group data, and on the influence of the chromatic and achromatic channels in apparent speed perception. The author also proposes two calibration procedures, which are necessary for the proper application of some of the proposed guidelines, regarding isoluminance and speed calibration. Application examples are also presented concerning data grouping and flow visualization.

It is also important to note that motion can sometimes be more effective to call users attention to a particular element of the visualization than just changing its color as shown by Bartram et al. [44,45] and therefore using both motion and color in concurrent ways, e.g., to highlight two objects, one using motion and the other using color (as opposed to Weiskopf's work where color is used to help convey motion), might lead to problems, for example, with the motion highlight diverting attention from the color highlight.

6.5. Audience, cultural connotations and context

It is important to have information about the target audience of a visualization, since it can provide some clues for color scale design. For example, conventions in one application area might place blue/violet colors of a spectrum scale at the low end (in order of increasing wavelength), while in another they may be placed at the high end (in order of increasing frequency) [16]. Therefore, paying attention to area conventions may make the process of designing the color scale easier and help avoid unintentional breaks with viewer expectations.

Furthermore, vision associated problems must also be considered, e.g., older people tend to be less sensitive to color. But one of the most common problems is color blindness. This is an important factor to have in mind, since it can seriously influence user performance by limiting the amount of information that can be extracted from color representations. This can be overcome by providing several parameters which users can adjust, while using hue as the only way of encoding information must be avoided. The literature [46] also describes several tests which can be used to detect color blindness problems in users.

Color can also have strong cultural connotations varying from culture to culture. Following such cultural conventions it is possible, for example, to reduce the cognitive load on the viewer or use connotations that suggest natural linkings between a variable or a variable value and the color used to represent it. For example, for an USA audience the color green is connected/ associated with the color of money; a natural connotation, when visualizing temperatures can be that of high temperatures represented in red and low temperatures in blue [16].

And what about the influence of culture in color cognition? Without going into much detail (given the complexity of the subject), there is active discussion regarding how culture and language might influence color cognition. On one side (among others), Berlin and Kay [48] argue that color cognition is innate and that color category perception/cognition is universal regardless of the language spoken. This is called the universalist view. On the other side, the relativist view (e.g., Saunders et al. [49]) argues that color cognition is a much more culture-related phenomenon and has pointed several flaws in Berlin and Kay's study regarding the methodology used and several a priori assumptions. Salomon et al. [31] state that cultural differences limit the number and categories of color recognized by an individual. Recently, Regier and Kay [50] argued that a purely universalist or relativist view on this subject cannot stand against recent findings and, thus, a new view gathering ideas from both sides might be a more proper approach.

Regarding color categories, Kawai et al. [51] have shown that the named category in which each individual color is inserted (by people) can influence perceived color difference, i.e., if two colors belong to the same named category (e.g., blue) their perceived difference will appear smaller than the perceived difference between two colors, at the same euclidean distance from each other, but in different color categories (e.g., blue and purple). For a good illustration of these effects and a description of obtained experimental results see Healey et al. [52]. The question remains regarding how the relativist view, considering color cognition is influenced by cultural issues, would influence these findings across cultures.

It is also important to understand the influence of external conditions and how adaptation mechanisms of the eye work: for example, the negative afterimage of what has been previously seen can result in visual stress from prolonged viewing; as well as the phenomenon of time dependent color perception influenced, for instance, by different environmental lightings [53] and display device properties. Providing adjustable parameters can be a good solution to deal with different output device characteristics. For instance, it is important to remember that the same RGB coordinates may result in slightly different colors in different output devices and, therefore, to render colors accurately some calibration process might be necessary.

Furthermore, the display device might influence our choice of color scale to meet, for example, power consumption goals in portable devices. Researchers have been striving to propose color scales which lower display device power consumption. A recent example is the work of Chuang et al. [54] which propose color scales allowing up to a 40% save in energy.

7. Learning through experimentation

In order to apply theoretical principles coming from other areas (such as psychophysics), verify the applicability of new principles, and find clues for the definition of new ones, many researchers have been conducting user studies [55].

Human color vision, a subject well studied (for more than a century now), provides strong clues for using color in visualization. However, the choice of colors for a particular task is more difficult, as it is far more complex, than the simple displays used by the experimental psychologists. So, experiments are necessary to fill the gap between theory and practice [55]. The main goal is to use well established theories to build design guidelines and then use an experiment to validate the guidelines in an applied setting.

7.1. Which Blair project

The work of Rogowitz et al. [47] presents a method which uses visual judgments to perceptually evaluate color scales. Since the literature points out that color scales which monotonically increase in luminance are good candidates for representing the magnitude of continuous data, the proposed method was designed to identify scales that include a monotonic luminance component. For that purpose, an image of a human face was used (Tony Blair), since it provides a structured visual pattern with gradual variations in luminance across its surface, thus providing the identification of irregular variations in the luminance of color scales.

The experiment started from eight color scales (shown in Fig. 7a) and, for each of them, seven additional scales where created, each subtending 25% of the original scale, which gave a total of 64 color scales. Fig. 7b shows the eight overlapping CIELAB greyscales created and how they looked when applied to Tony Blair's image.

During the experiment, users were shown 32 pictures randomly ordered for each observer (Fig. 7c shows an example of part of one of the image matrices used). They then had to rate each picture according to the degree to which the image appeared to be a recognizable photograph of a face. The obtained results seemed to show that the proposed method may function as a quick procedure of identifying color scales with monotonically increasing luminance with the advantage that it does not require display calibration or lengthy psychophysical procedures.

7.2. Face-based luminance matching

The work of Kindlmann et al. [56] is similar to the one presented by Rogowitz et al. [47]. They address the problem of color scale luminance control by proposing a novel technique for luminance matching. Their technique, given a fixed reference color, and a test color with brightness varied by the user, allows matching the luminance of both. They use images of faces in their experiment since they want to take advantage of humans being good at recognizing faces, due to brain circuitry dedicated to this process [57].

Their method starts by a black-and-white thresholded image of a human face: shadows in black and directly lit areas in white. The test pattern is then composed by the images in Fig. 8 which also include a reverse image. Next, they replace black with a shade of grey and white with a color. According to the luminance of the colored region, in comparison with the luminance of the chosen grey, one of the faces will appear positive and the other negative.

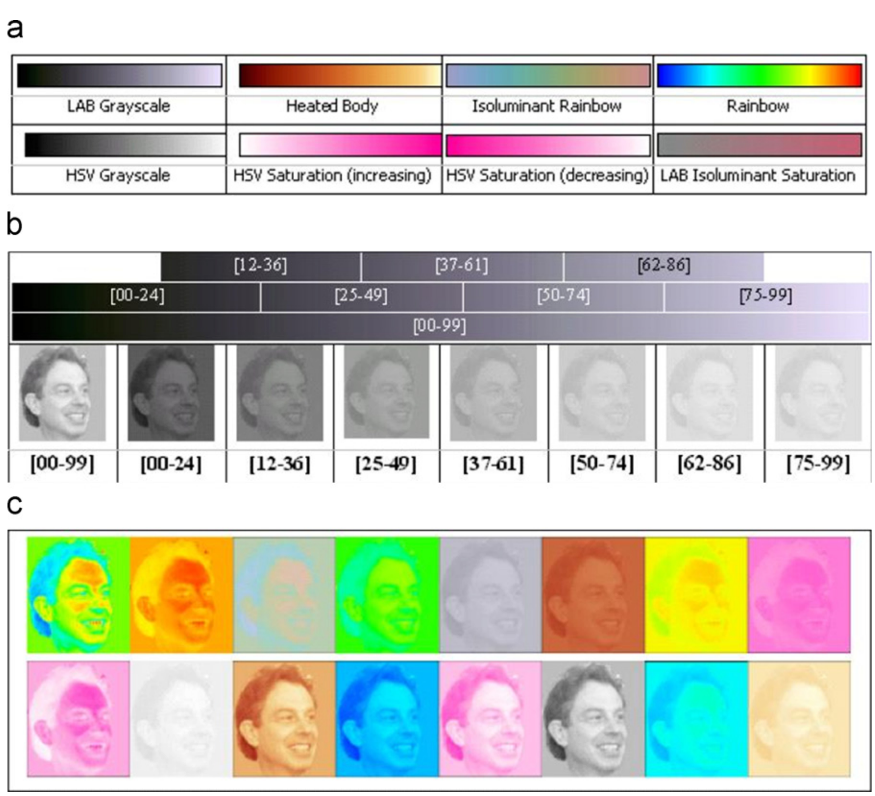

Fig. 7. (a) The eight color scales used in the Which Blair Project [47]; (b) The eight overlapping LAB greyscales (top) and the results of applying them to the Blair photograph and; (c) An example of a faces matrix used in the experiment. Reproduced with permission from [47]. © 2001 IEEE.

For example, in Fig. 8 the left face is positive. Therefore, to match the luminance between the two regions it is only necessary to adjust the intensity of the grey or color region until the point where none of the faces appears positive or negative.

The authors claim that their method provides very good results and enables the creation of color scales, with any pre-determined pattern of luminance, in devices (e.g., monitors) which are not calibrated.

7.3. Other examples

Other examples are the work of Ware [20], which leads to some rules guiding the process of color scale construction, of Healey [58], which presents a technique for effectively choosing multiple colors for use during data visualization, and of Montag [59], where the performance in judging values in univariate maps encoded using five different color scales is tested.

Fig. 8. Double face image. Reproduced with permission from [56]. © 2002 IEEE.

8. Auxiliary tools and methods

During the past few years some efforts have been made in order to provide users (in particular non-experts) with tools and methods which allow them to select an appropriate color scale for their particular visualization purpose.

8.1. Dynamic exploration of color mappings

Rheingans et al. [60] propose a tool which allows the exploration of data sets by interactively manipulating the color scale. On the upper left of the screen appears the image space which shows the currently selected color scale applied to the data. In the center of the screen a 3D color space appears and a curve, within it, shows the path defining the sequence of colors composing the color scale. As the path in the 3D color space is modified, the image is dynamically changed accordingly.

8.2. PRAVDAColor

Bergman et al. [33] present a tool called *PRAVDAColor* which focuses on helping users to select color scales. With that purpose, they have built a library of color scales and defined a set of perceptual rules which allow selecting appropriate maps according to the structure of the data and visualization goal. They present a taxonomy for color scale selection which guides their work: starting from the type (ratio, interval, ordinal or nominal) and spatial frequency of the data, and according to the representation

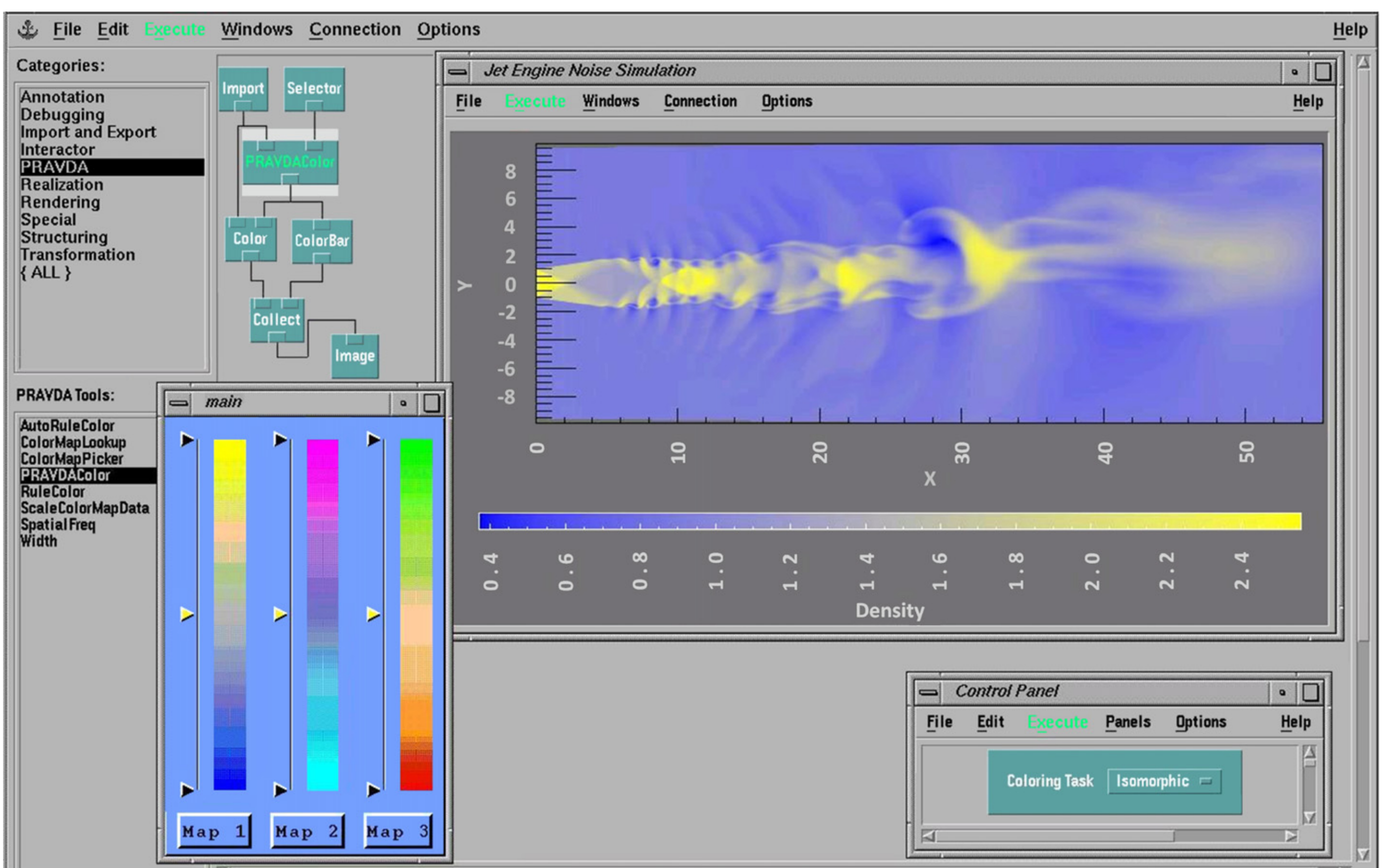

Fig. 9. A screen capture showing *PRAVDAColor* integrated in the *Data Explorer* environment. Reproduced with permission from [33]. © 1995 IEEE. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

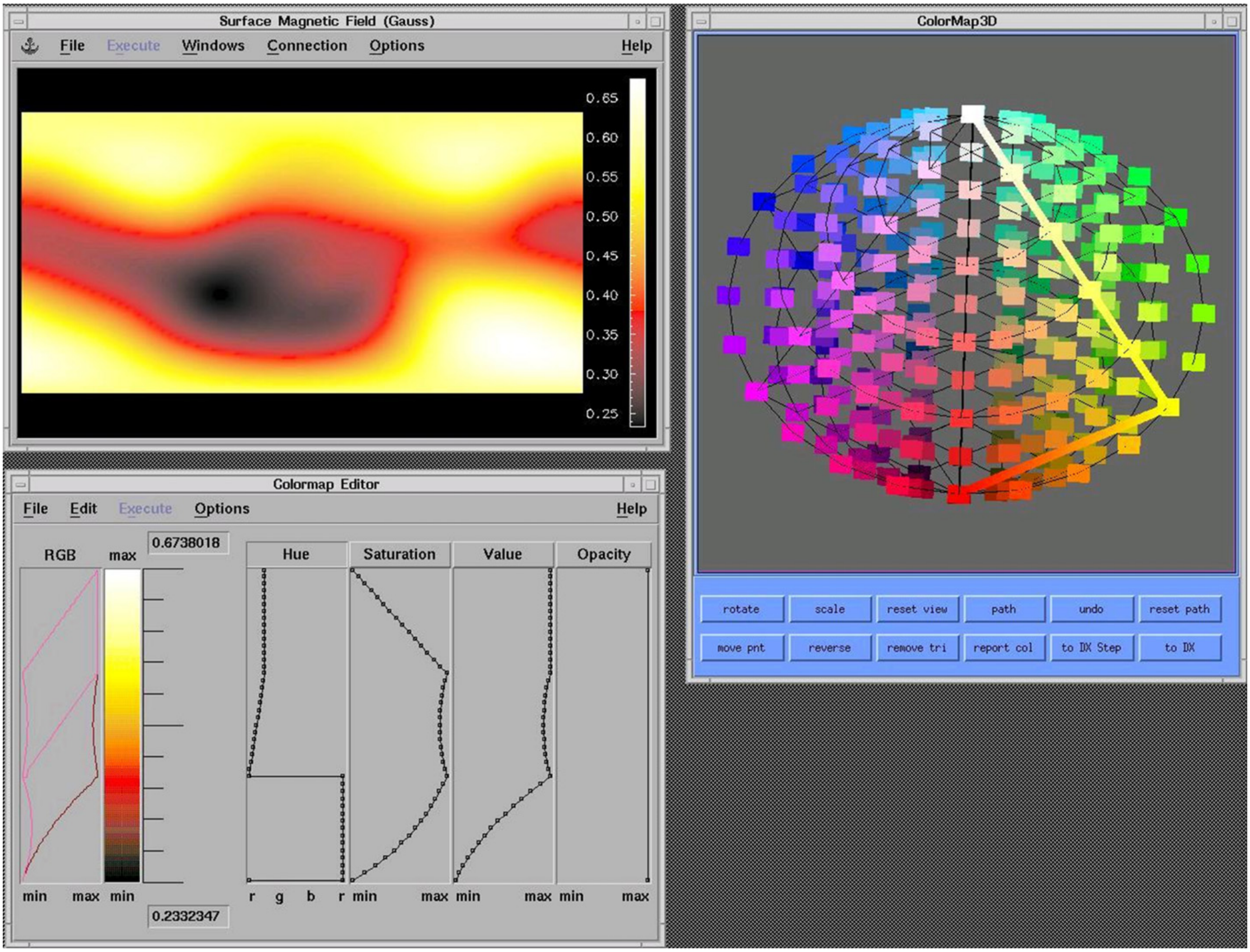

Fig. 10. Three-dimensional color scale construction tool. Reproduced with permission from [33]. © 1995 IEEE. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

task (isomorphic, segmentation or highlight), several guidelines are proposed (see Bergman et al. [33]).

Fig. 9 shows *PRAVDAColor* integrated in the *Data Explorer* environment. With *PRAVDAColor* the user is presented a set of color scales judged appropriate to the data set (based essentially on the data spatial frequency, but also on the presence/absence of a zero crossing in order to distinguish between ratio and interval data) and task. At first, one of those color scales is automatically applied to the data in order to produce a first representation, then the user can freely apply any other of the available color scales to the data. It is also possible to control the way the color scale is mapped onto the data by defining to which colors the data minimum, maximum and midpoint values will be mapped.

To build the color scales another tool is also available (similar to the one proposed by [60]).[1] It is a 3D color scale builder. The user can interactively build a path along a hue–lightness–saturation (*HLS*) double cone (Fig. 10). This tool provides undo and move functions for editing that path. It is then possible to use the created color scale along the *Data Explorer* pipeline. The output color scale can be a linear interpolation between the selected points on the *HLS* space, or the user may obtain a discrete color scale, with equally sized segments, for each selected point (which may be suitable for segmented representation tasks).

8.3. ColorBrewer

ColorBrewer [29] (recently updated to its version 2.0), developed using Macromedia's Flash, is not exactly a tool to create color scales or directly decide the better color scale for a data set. Instead, it provides an environment and a set of color scales to help users choose the best color options for maps (see Fig. 11).

The process starts by defining the number of data classes the user wants to represent. Then, he chooses the type of legend: sequential, diverging or qualitative. After that, some legends are presented using different color schemes and the user can choose among them. An example map is then colored according to the user's choice. It is possible to modify several map parameters: activate/deactivate a road network, city symbols, or region borders and their colors (using the interface presented in Fig. 12); zoom; and modify the color with which each of these parameters appear.

[1] For recent information on 3D color pickers see Wu et al. [61].

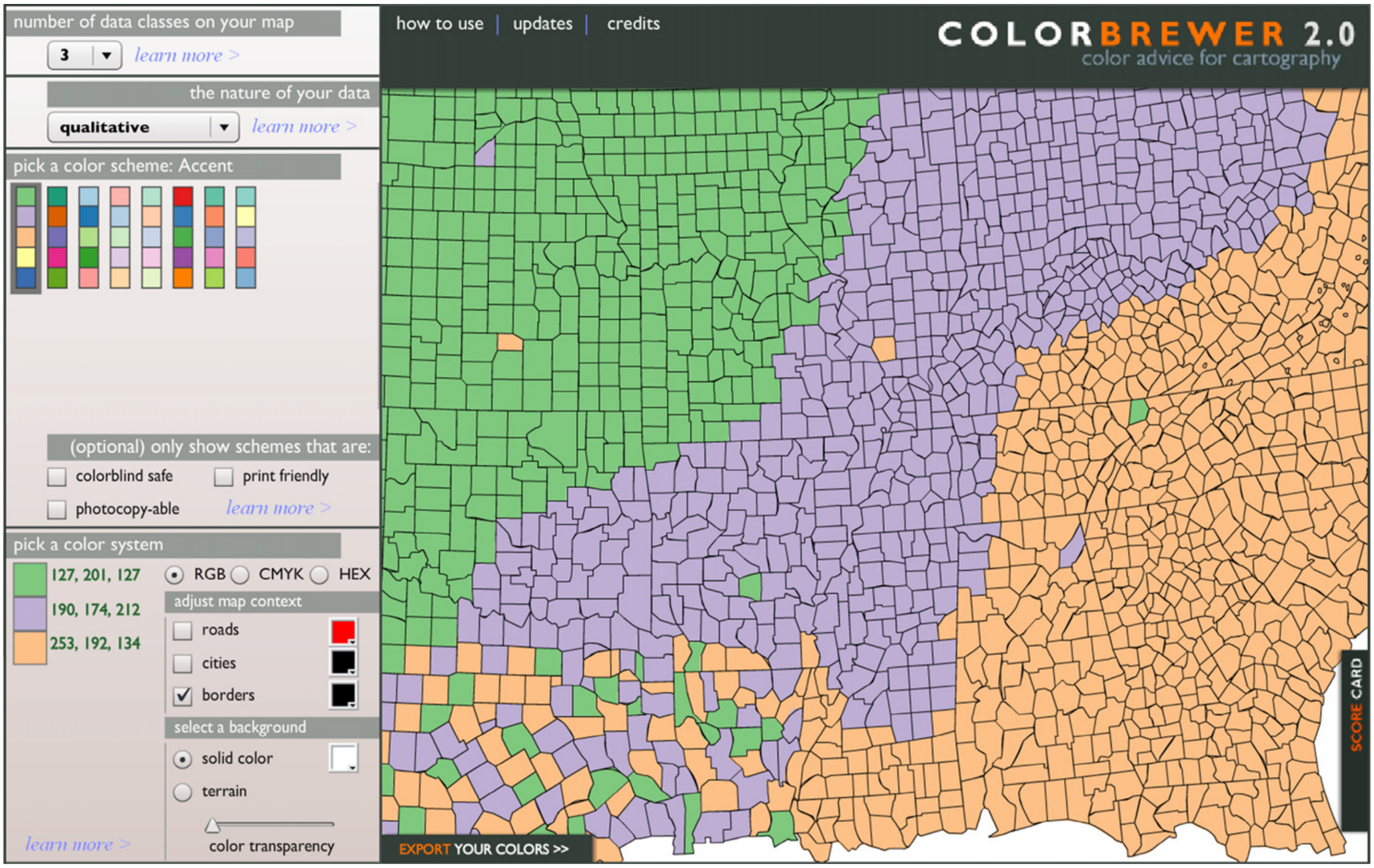

Fig. 11. ColorBrewer's interface [29]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

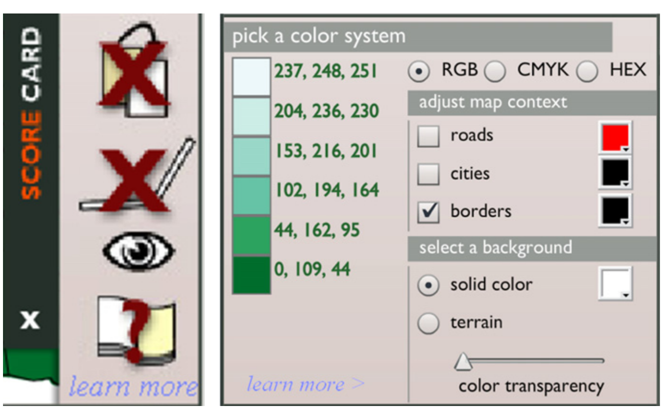

Fig. 12. ColorBrewer's interface details [29]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

This tool also provides an interesting feature: it informs the user about some properties of the chosen representation, namely:

1. If it is suitable for color blind people.
2. If it will withstand black and white photocopying.
3. If it is suitable to view on LCD monitors.
4. If it is color printing friendly (according to tests made on some printers).

This information is provided by the symbols presented on the left of Fig. 12 (a red cross over a symbol means that the chosen color scheme does not support that property).

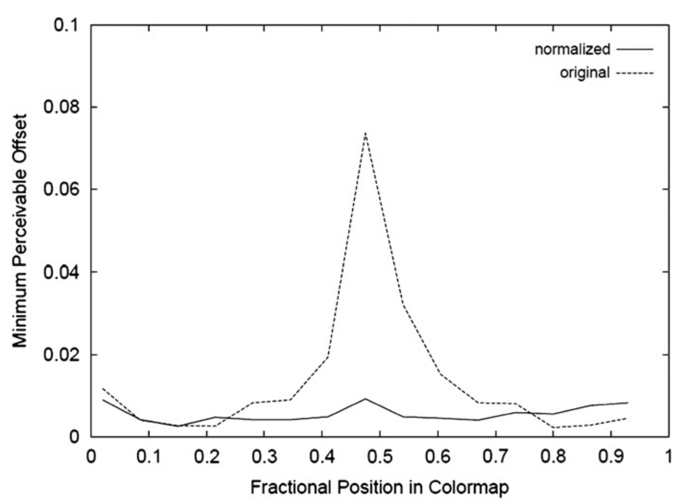

Fig. 13. Measured perception function for a rainbow color scale and for a normalized rainbow color scale. Reproduced with permission from [62].

In the interface area presented on the right of Fig. 12 it is possible to see the chosen color scheme and obtain the parameters defining each color using one of two color models (RGB and CMYK). The appearance of roads, cities and region borders can also be enable/disabled in this area and the color for each of these elements can be chosen. A new feature in ColorBrewer 2.0 is the ability to select a background for the map (a solid color or terrain data) and then choose the level of transparency applied to the overlayed data.

The limitation of this tool is the fact that there is no possibility of using a different data set to perform the testing.

8.4. Self-corrected perceptual colormaps

Gresh [62] presents an algorithm which, given a particular color scale, transforms it into one that is more perceptually uniform, i.e., equal steps in data values are equally perceived.

The perception function for a particular user on a given monitor is experimentally measured and then, based on those results, the color scale is modified to make it as uniform as possible. Fig. 13 shows the original measured perception function and the perception function measured for a normalized rainbow color scale. Notice how the new color scale presents a flatter perception function.

Fig. 14 shows, on the left, a standard rainbow color scale applied to a topographic data set and, on the right, the same data set colored with the obtained normalized rainbow color scale. It is possible to perceive more detail in the image on the right, specially in the blue region and a reduction of the green region.

8.5. Enhancing visual exploration by appropriate color coding

The work of Schulze-Wollgast et al. [63] extends the methods proposed by Bergman et al. [33] by extracting statistical metadata from the data set, and then using that information to adapt the chosen color scale.

The used metadata consists in the average, median, mode, minimum, maximum, skewness and quartiles of the data set. While all these values can be computed for quantitative data, only a subset can be computed for ordinal and nominal data. In the latter case, only the mode can be computed.

Based on such data several automatic color scale modifications may occur which include adjusting control points for setting an appropriate mapping function.

Fig. 15 shows how a color scale has been adjusted for a segmentation task by positioning control points according to boxplot quartile position.

Changing the mapping function may be necessary to correctly deal with certain data distributions. Linear interpolation between control points is the most common approach, but can lead to problems if the data are not uniformly distributed (e.g., due to outliers), in which case the scale is stretched leading to unnoticeable differences between close values. This is solved by using nonlinear mapping functions. The decision is supported by analysing the skewness of the data distribution: if it is positive an exponential mapping function is used; if it is negative a logarithmic mapping function. Fig. 15, on the right, shows how

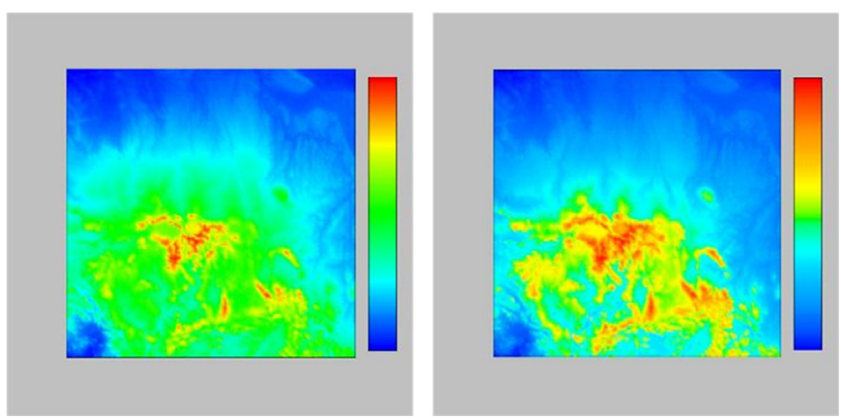

Fig. 14. Left, standard rainbow color scale applied to a topographic data; right, a normalized rainbow color scale applied to the same data. Reproduced with permission from [62]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

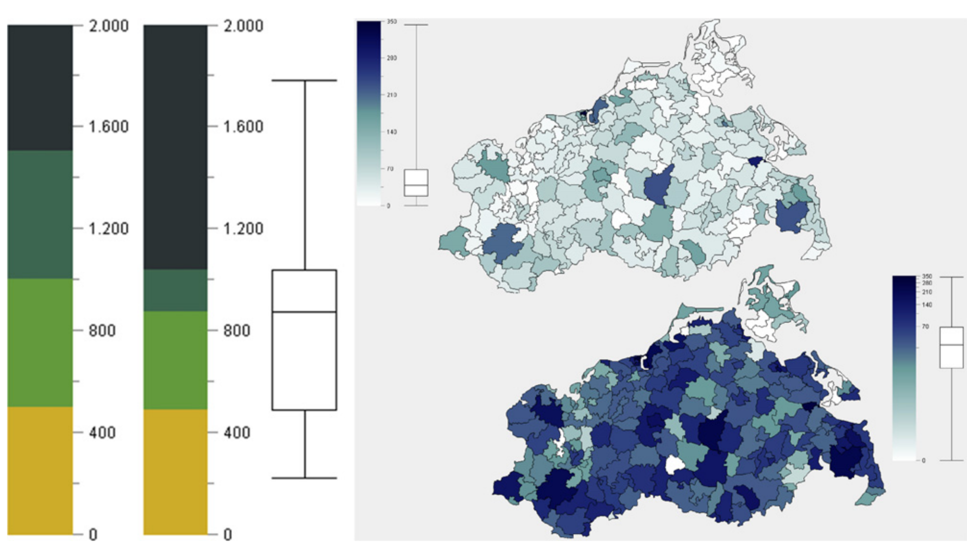

Fig. 15. On the left, color scale adapted for a segmentation task according to boxplot quartiles; on the right, changing the mapping function allowed a proper comparison of different regions. Reproduced with permission from [63]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

changing the mapping function allows a better comparison among regions.

Another feature presented by Schulze-Wollgast et al. [63] is a color legend which includes a boxplot side-by-side with the color scale, thus providing a better insight on the data distribution. This feature can be observed in Fig. 15.

8.6. VisCheck and Daltonize

VisCheck [64] is a tool which shows how an image or site is seen by an user with some kind of colorblindness. It is possible to choose among three different types of vision deficiencies, deuteranope (red/green deficit), protanope (another red/green deficit) and tritanope (blue/yellow deficit), and then see how it influences the perceived colors.

Daltonize [65] is a tool which allows correcting a particular image in order to allow a better perception of color differences by users with vision deficiencies.

8.7. Other examples

Other examples are the work of Hyun [66], which deals with the creation and usage of non-linear color scales, and of Ventura et al. [67], which deals with the problem of ordered/unordered color scales, and its generation in a device-independent color space, through a computer-aided color coding system based on fundamental principles of human vision.

9. Conclusion

Given the importance of color in data and information visualization, an overview of relevant work regarding the use of color in visualization scenarios is presented. From surveyed literature, it is clear that more detailed knowledge is of paramount importance for an informed use of color in visualization. The guidelines proposed by several authors do not provide a solution for all scenarios, but help users to understand the advantages and disadvantages of using particular color scales in specific situations, and contribute for a greater awareness to possible issues in their visualizations. The fact that these guidelines are produced with the support of experimental work is very important, as it increases their value and helps in understanding the subjacent concepts and ideas.

The tools proposed to help create color scales which are suited for particular data or visualization goals, or which provide environments where color scales can be applied to data using specific taxonomies, allow that several of those guidelines be transparently (or, at least, with some support) applied by users.

But, even though these guidelines and tools exist, they are not being systematically used by practitioners. In fact, one of the most problematic color scales known (the rainbow color scale) is still the most used in visualization tools [4]. Therefore, efforts must be made to motivate the community to pay more attention to the issues related with color usage in visualization, and to justify their choices with more than an aesthetic motive.

The surveyed literature also reveals how important it is to learn with the work of others and will hopefully motivate researchers to share their experiences in different application areas where visualization is present.

By presenting this survey, we aim to provide a contribution to such efforts.

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