

Task-Driven Color Coding

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Abstract

Color coding is a widely used visualization method for scalar data. To generate expressive and effective visual representations, it is extremely important to carefully design the mapping from data to color. In this paper, we describe a color coding approach that accounts for the different tasks users might pursue when analyzing data. Our task description is based on the task model of Andrienko & Andrienko [1]. We apply different color scales and introduce strategies to adapt the color mapping function to support tasks like comparison, localization, or identification of data values.

Keywords—**Visualization, Color, Task.**

1 Introduction and Motivation

Color coding is a fundamental visualization method for representing scalar values, and is therefore widely used in a large variety of application scenarios. Designing appropriate color scales is an intricate step that influences the expressiveness and effectiveness of visual representations significantly. *Appropriate* in this context means that the color-coded visualization really supports analysts in deriving assured statements about the underlying data. Appropriateness can only be achieved if characteristics of the data and the tasks of analysts are taken into account. Therefore, it is necessary to provide flexible color schemes that can be adapted to the data and task at hand.

Generally, a color coding scheme can be characterized by a color mapping function $f : D \rightarrow C$ that maps data values D to colors from the color scale C . From literature we know several approaches that address adequate definition of the color mapping function, or give guidelines for the use of color scales. In this context, Cynthia Brewer’s *ColorBrewer* has to be mentioned as a pioneer work [4, 5, 8]. Brewer describes binary, qualitative, sequential, and diverging color scales for visualization on cartographic maps. A major point of Brewer’s work is that these scales are based on human perception, and that they have been evaluated for different output devices like CRT screens, TFT displays, or LCD projectors.

However, the *ColorBrewer* was specifically designed for segmented maps; continuous data is not supported. Continuous color scales are considered in the *PRAVDAColor* tool from Bergman et al. [2]. Additionally, the tool offers a rule-based mechanism to support users in choosing appropriate color scales. The mechanism is based on data characteristics (data type: ratio / interval data; spatial frequency: low / high) and visualization tasks (isomorphism, representation, segmentation, or highlighting). In Schulze-Wollgast et al. [12], the influence of data characteristics (e.g., the distribution of data values) on color coding is investigated in more detail. Based on the extraction of statistical meta-data like average, median, and extreme values as well as skewness and quartiles, the color mapping function is adapted to be consistent with the characteristics of the data range. Schulze-Wollgast et al. further enrich the color-coded visualization by an expressive color legend, including a Box-Whisker plot to communicate data features. Furthermore, the problem of color coding for the purpose of visual comparison is discussed. While the color mapping function f usually employs linear interpolation, Hyun has experimented with nonlinear functions to improve interactive data exploration [9].

More general overviews on the color coding problem are given in [14] and [15], including aspects of basic vision and psychophysics, color reproduction, and color design.

In this paper, we will discuss color coding with regard to the task at hand. Previous publications, like [2] or [12], address the design of color scales for specific tasks (e.g., isomorphic, segmentation, comparison), while others, like [10] or [16], just point out that the goal of the user has to be considered when using color coding. However, to the best of our knowledge, a systematic approach for a task-driven color coding still has not been published. We take on this issue and propose a generic view on the problem. Our work is based on the task description of Andrienko & Andrienko [1], which served as a good starting point to think about tasks and color-based visualization.

To lay a common ground, we review aspects that influence the design of color coding schemes in Section 2 and briefly introduce the task model in Section 3, where we

also identify the main aspects of task-driven color coding. In Section 4, we discuss the color coding problem in more detail. We conclude with a short summary and an outlook on future work in Section 5.

2 Requirements for Color Coding

A fundamental requirement for effective color coding is that the color mapping function f has to be invertible. This means that every data value (or every well-defined group of data values) is associated with exactly one color, and vice versa, every color represents a fixed range of data values. In other words, colors encoded from two different data values should be visually distinguishable. On the other hand, visually similar colors imply that they represent data values that are close to each other. Moreover, if the data's value range is given by a linear function, the color mapping function has to be constructed in such a way that the color coding is *perceived* as linear as well; just linearly mapping the components of the color space in use is not sufficient, particularly when using the RGB color space. Otherwise, perceptual variations in the visual representation do not express the true magnitude of variation in the underlying data.

Besides these basic requirements, further aspects decide about effectiveness of color coding. Telea identifies the following factors to be relevant for color coding [16]:

Characteristics of the data: Statistical features, overall distribution of data values, as well as data variation speeds and domain sampling frequencies are data characteristics that should be considered when designing color coding schemes. For example, using a linear color mapping function on a skewed data set will result in the majority of data values being compressed to a narrow range of colors. Depending on the task at hand, this can be disadvantageous (see [12]).

Characteristics of tasks and goals: Different tasks and goals require different color coding schemes. A main distinction here is whether the task requires the comparison of exact values (i.e., quantitative analysis) or the judgment of qualitative differences. Furthermore, certain goals may lead to specific regions of interest in the data domain. These regions should be accentuated, for instance by using bright, warm, and fully saturated colors. The appropriate selection of color scales according to four specific tasks is discussed in [2]. In Section 4, we will introduce our approach to task-driven color coding.

Characteristics of the user: Although color coding is a commonly applied method, the capabilities and the cultural as well as professional background of users are only rarely considered to an adequate level. Individual color perception varies from user to user, which makes it necessary to check the color perception capabilities of users

before presenting color-coded images [7]. For users suffering from color blindness, data values have to be mapped redundantly to visual variables others than color. An example for variance in the professional background is the placement of blue/violet colors in a spectrum scale [10]. In some fields these colors may be placed at the low end of the color scale (in order of increasing wavelength), in others at the high end (in order of increasing frequency).

Characteristics of the output device: Different output devices use different systems to define and display colors. Thus, a color coding scheme being appropriate for displaying data on a computer display might be inappropriate to show the same data on printed materials. Therefore, the color scales of the ColorBrewer were evaluated for different output devices (see [4, 5]).

The aforementioned criteria address four questions: *What* is visualized (data), *why* and for *whom* is it visualized (task respectively user), and *where* is the output displayed (device). The problem is that many visualizations that use color do not consider these four questions to an adequate level. It is often the case that just basic color coding schemes are used, most prominently the classic rainbow color scale. However, such methods can lead to a variety of problems [3, 13]. Our goal is to shed some light on more advanced color coding schemes. In particular, we investigate the *why* aspect in more detail and present our preliminary findings.

3 Specification of the Task at Hand

Task-driven color coding requires task descriptions as a basis. Most early task descriptions are given as verbal lists of visualization goals, including identification, correlation, comparison, and others. These descriptions lack formal description, and hence, concrete understanding of the tasks can vary. Recently, Andrienko & Andrienko proposed a task model that is based on formal definitions [1]. This allows for a precise view on visualization tasks. We believe that developing task-driven color coding based on a task model with a formal background is a good initial choice.

The formalism behind the task model of Andrienko & Andrienko uses two basic notions: *references*, the space where data values have been collected, and *characteristics*, the space of attributes that were collected. This distinction is in line with the well-known distinction of independent variables and dependent variables.

On its first level, the task model distinguishes two classes of tasks: *elementary* and *synoptic* tasks. Elementary tasks address individual data elements. This may include groups of data, but the main point is that data values are taken into account separately and are not considered as a whole. Synoptic tasks, on the other hand, involve a general view and consider sets of values in their entirety.

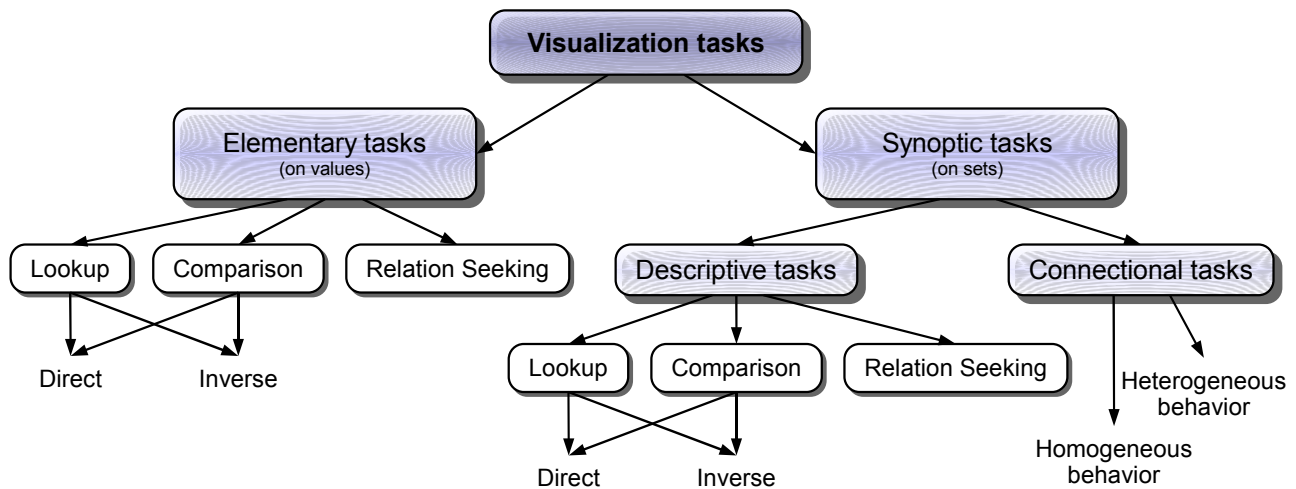


Figure 1: Task typology (adapted from [1]).

Elementary tasks are further divided into *lookup*, *comparison*, and *relation seeking*. The lookup task defines a search for data characteristics. This includes both direct and inverse lookup, depending on if references are given and corresponding data values are sought (also referred to as *identification*), or data values are given and associated references are of interest (also called *localization*). Relation seeking tasks search for occurrences of relations specified between data characteristics or references. In a broader sense, comparison can also be seen as relation seeking, but the relations to be determined are not specified beforehand. Direct comparison tasks relate characteristics, whereas inverse comparison tasks search for relations between references.

Synoptic tasks are divided into *descriptive* and *connectional* tasks. Descriptive tasks specify the properties of either a set of references or a set of characteristics. The first case belongs to the group of *identification* tasks. Here, a set of references is given, and the task is to find a pattern that describes the behavior of the given reference points. The second case belongs to the group of *localization* tasks. Here, a concrete pattern is given, and the task is to search for those reference points that exhibit the pattern. Besides specifying the properties of a set of characteristics or references, the *comparison* of those sets is of high relevance. As in the case of elementary tasks, we have to distinguish between direct and inverse comparison tasks, depending on whether a set of references or a set of characteristics is compared. Moreover, the synoptic task *relation seeking* considers two sets of characteristics or references to come up with relationships between these sets. In contrast to descriptive tasks, connectional tasks establish connections between at least two sets taking into account the relational behavior of two or more variables. Depending on the

set of underlying references – either variables are considered over the same set or over different sets of references – *homogenous* and *heterogeneous* behavior tasks are distinguished.

The aforementioned tasks are arranged in a task topology, summarized in Figure 1. To achieve task-driven color coding, we have to identify color maps that are appropriate for the different tasks. The first-level categorization of tasks draws a distinction between individual data values and sets of data values. This can be reflected by applying either continuous/discrete color scales, where each data value is encoded by a separate color, or segmented color scales, where each color stands for a set of data values. At the second level, the tasks lookup and comparison are particularly of interest with regard to the color coding problem (see [12]). The lookup task requires color scales that support accentuation of particular color values. In order to accomplish comparison tasks, all variables involved in the comparison must be represented by a unified color coding scheme; perceptual separation of colors for the individual variables is not the primary goal here. Usually, the same holds true for relation seeking and connectional tasks. The third level addresses identification and localization tasks. Both problems demand for different color scales: identification (direct lookup or direct comparison) requires recognizing characteristics as precisely as possible, whereas localization (inverse lookup or inverse comparison) requires easy recognition of those spatial references that exhibit certain characteristics of interest. In the latter case, color coding schemes that support accentuation and de-accentuation are suitable. At the bottom line we have to consider three alternatives to come up with an initial approach to task-driven color coding:



Figure 2: Unsegmented and segmented color scales for identification and localization.

1. Individual values vs. sets of values,
2. Identification vs. localization.
3. Lookup vs. comparison, and

In the following section, we will discuss color coding schemes for these alternatives in more detail.

4 Color Coding for Specific Tasks

Color coding individual data values requires unsegmented color scales, that is, every color $c \in C$ represents exactly one value in $d \in D$. In contrast to that, segmented color scales should be used to encode groups of data values, that is, every color in $c \in C$ represents a subset $D' \subset D$. The specification of both of these types of color scales is a well investigated problem [2, 8, 13]. Figure 2 shows examples of unsegmented and segmented color scales for the identification and the localization task. The segmented color scale for identification represents five different value sets. The color scales for localization are designed in such a way that they support preattentive recognition of reference areas of interest. The segmented color scale for localization supports a binary decision: Areas drawn yellowish match the selection criteria, other areas do not. The unsegmented color scale communicates a smooth selection of reference areas comparable to smooth brushing [6].

Designing appropriate color maps for lookup and comparison tasks requires additional effort. We will introduce two new concepts for this purpose next.

4.1 Color Scales for the Lookup Task

Lookup tasks are basically a search for concrete characteristics or references. This search can be facilitated by applying appropriate color coding schemes. While the inverse lookup task is relatively easy to handle, the design of adequate color scales for direct lookup is intricate. Schulze-Wolgast et al. propose the extraction of statistical meta data to adapt a given color scale accordingly [12]. The adaptation process includes three steps: 1) Expansion of the value range to be mapped onto the color scale

such that the lower and upper bounds are intuitive to interpret, 2) adjustment of control points of the color mapping function to improve the color coding for data-dependent segmentation or highlighting, and 3) skewing of the color mapping function (e.g., applying logarithmic or exponential mapping functions, rather than linear ones) to handle data ranges with special value distributions. Here, we introduce two approaches to improve color coding for the lookup task: *histogram equalization* and *Box-Whisker plot adaptation*. Both methods address the problem that certain value distributions can lead to situations where the majority of data values is represented by only a narrow range of colors. This is unfavorable for lookup tasks. By histogram equalization and Box-Whisker plot adaptation, we spread the colors according to the data's value distribution and achieve that more colors are distinguishable in dense parts of the data.

Histogram equalization: Histogram equalization was originally introduced to improve the contrast of gray-scale images. The same concept can be used to adapt a given color scale according to the value distribution of the data at hand, and thus, to improve the perceptibility of the color-coded visualization. The procedure can be described as follows. First, the value range is subdivided into uniform bins, and the number of data values falling into the bins is computed. Second, the color scale is sampled according to the same uniform subdivision. The corresponding sample points, which represent specific colors, are then shifted based on the computed cumulative frequencies. Finally, a linear color mapping function is applied to establish a continuous color scale. As a result, more colors are provided for those segments that contain a higher number of data values, making values in high density regions easier to distinguish.

Box-Whisker plot adaptation: An alternative procedure to adapt the color coding to the characteristics of the value distribution is to utilize Box-Whisker plots. Box-Whisker-Plot adaptation subdivides the data range based on quartiles and inter quartile range (IQR), which are commonly accepted features to describe value distribution. Quartiles and IQR are more robust against outliers than other statistical indicators. The Box-Whisker plot segmen-

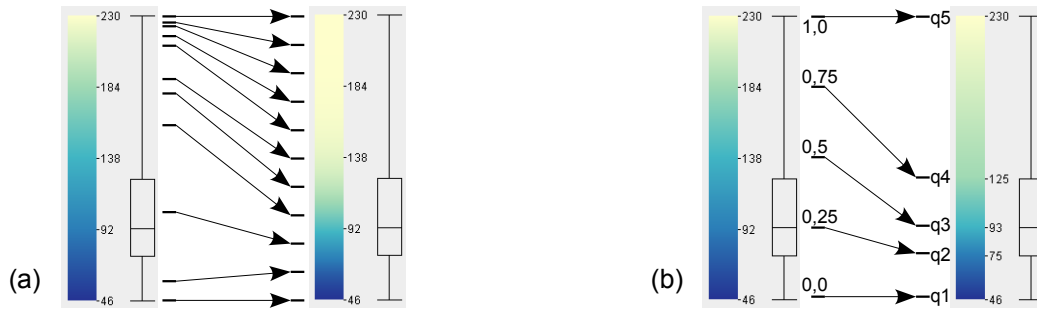


Figure 3: Adaptation of color maps. (a) Histogram equalized color map; (b) Box-Whisker plot adaptation; Additional Box-Whisker plots visualize the data distribution.

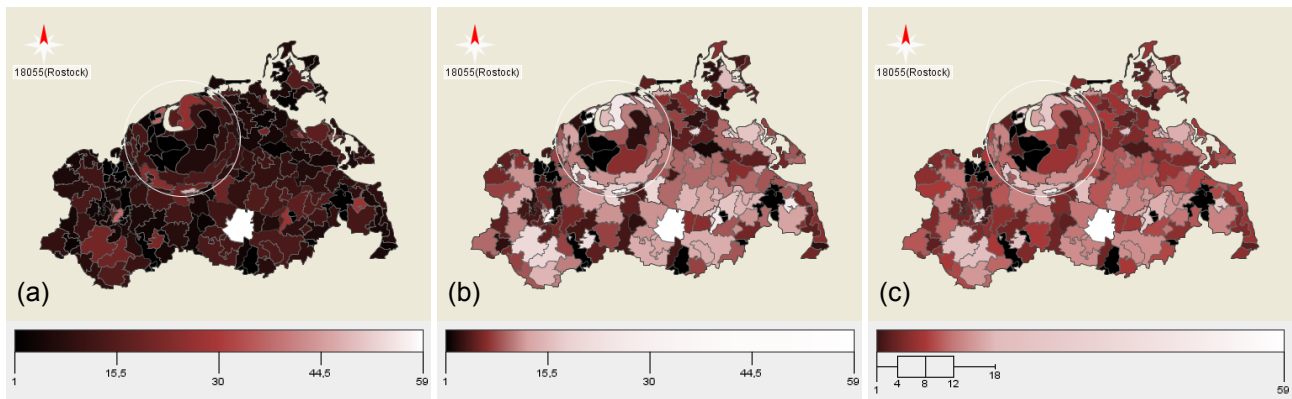


Figure 4: Visualization of quantitative data on a map. (a) Classic linear color coding; (b) histogram-equalized color coding; (c) color coding adapted based on Box-Whisker plot.

tation reflects the underlying data distribution closely, and hence, also leads to improved color coding.

Figure 3 compares the segmentation strategies of histogram equalization and Box-Whisker plot adaptation. Visualization examples generated without and with the proposed methods are given in Figure 4. It can be seen that colors are hard to distinguish in dense parts of the data (a). By applying our adaptation methods, more colors are assigned to these dense parts, and hence, colors can be discerned more easily (b) + (c). It is important to mention that we deliberately relinquish linearity of the color scale in favor of separability of colors in dense regions.

4.2 Color Scales for the Comparison Task

The comparison of two or more attributes requires a global color coding scheme that guarantees that equal colors stand for equal values. This leads to problems, in particular, if the value ranges of the attributes to be compared are quite different. In such cases, an attribute with a smaller value range would be represented by only a very small region of the global color scale. The goal now is to improve the differentiability of colors for these small value ranges.

We handle this problem by merging overlapping value ranges. The result of this process are fewer distinct value ranges that do not share common intervals. Now, for each distinct value range a separate color scale is designed. Since the newly defined ranges do not overlap, it is possible to assign a separate hue to each, while varying only brightness and saturation to define the color coding. These separately specified color scales are integrated into one global scale (see Figure 5(a)). To avoid inconsistencies, it must be guaranteed that the brightness and saturation values of the boundary of one color scale correspond to the respective values of the neighboring scale. In other words, for one value range the hue is constant while brightness and saturation vary, whereas at the boundary from one value range to the next the hue varies while brightness and saturation are equal (see Figure 5(b)). This way, even small value intervals will be represented by their own brightness-varying subrange of the global color scale and the differentiation of data values is improved.

Figure 6 shows how different color coding schemes influence the task of comparing three attributes of a data set. Figure 6(a) uses individual color scales for each attribute.

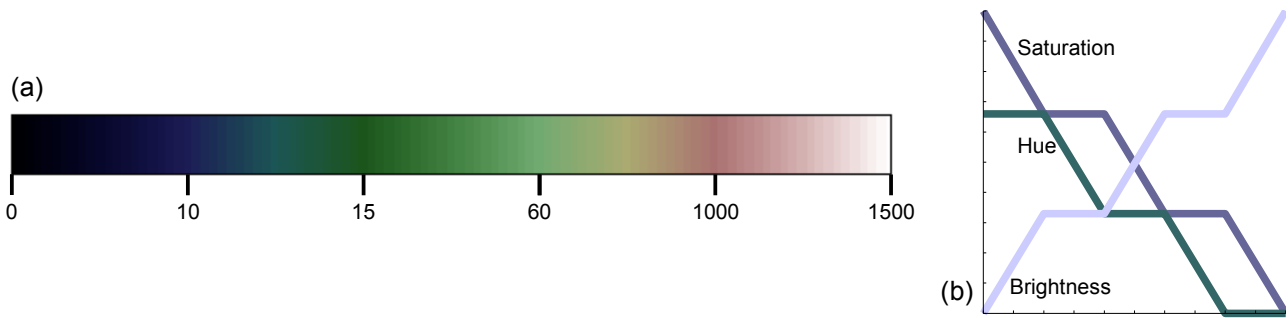


Figure 5: Color scale for comparison tasks. The five value ranges $[0,10]$, $[20,50]$, $[15,30]$, $[40,60]$, and $[1000,1500]$ were merged resulting in the three distinct ranges $[0,10]$, $[15,60]$, and $[1000,1500]$. Each distinct ranges is assigned with a distinct hue blue, green, and red, respectively. (a) Generated comparison color map; (b) its definition in the HSB color space.

Visual comparison is hardly possible because one and the same color represents three different data values (one in each value range). A global color scale as shown in Figure 6(b) allows for visual comparison, but data values of the first and third attribute are no longer distinguishable because their value ranges are rather small compared to the one of the second attribute. Applying Box-Whisker plot adaptation helps to improve perception, but the results presented in Figure 6(c) are not really convincing. The approach we introduced in the previous paragraph delivers better results (see Figure 6(d)). Values of the first and second attribute are easier to identify and to compare. However, the third variable is still hard to perceive.

Figure 6 shows the potential, but also the limits of our approach to support comparison tasks. The problem is that we cannot yet guarantee that adequate color scales will be generated in all cases. In particular, if the merging process generates too many or too few distinct value ranges, the problem becomes apparent. In the former case, it would be difficult to assign distinguishable hues for each value range. In the latter case, it could be possible that small value ranges are merged into huge ranges nonetheless, and thus are still represented by only a few colors.

We conclude that achieving appropriate color coding for comparison tasks is a challenging problem and requires further investigation. Our approach can be seen as a first step towards a general solution.

4.3 The Task-Color-Cube

As a summary of the previous discussions, Figure 7 shows the task-color-cube. The three task alternatives introduced at the end of Section 3 span a 3-dimensional space with eight discrete points. Each of these points represents a specific task and requires a specific color coding scheme to achieve expressive visualization. We assigned color coding schemes to each corner of the task-color-cube based on the following guidelines:

1. Individual data values vs. sets of data values: unsegmented vs. segmented color maps.
2. Lookup vs. comparison: several separate color maps vs. one global color map.
3. Identification vs. localization: color scale that match data characteristics vs. color scale that accentuates ranges of interest.

5 Concluding Remarks

Color coding is a fundamental and widely used visualization method. Numerous studies on this subject identified key aspects of color scale design and provided guidelines for developers to make appropriate choices of color scales for expressive and effective visualizations. However, even though it is commonly accepted that different tasks require different visualizations, so far no systematic approach to task-driven color coding had been developed. For this reason, we presented here color coding concepts that address different visualization tasks derived from a formal task typology. Our concepts are choose from different color scales and adapt color mapping functions according to tasks and data characteristics. Since color perception is always dependent on the user, all our methods are subject to interactive refinement. Interactively adjusting the color coding is particularly useful when exploring unknown data.

There are three aspects pertaining to color coding in general that have not been discussed in this paper. First, only two-dimensional visualizations have been considered. Three-dimensional representations impose different constraints. For example, brightness variations resulting from lighting and shading in 3D is likely to interfere with brightness variations inherent to the color scale used for the visual encoding of data (see [13]).

Second, in the course of the detailed discussion of our approach in Section 4, we presumed dealing with quanti-

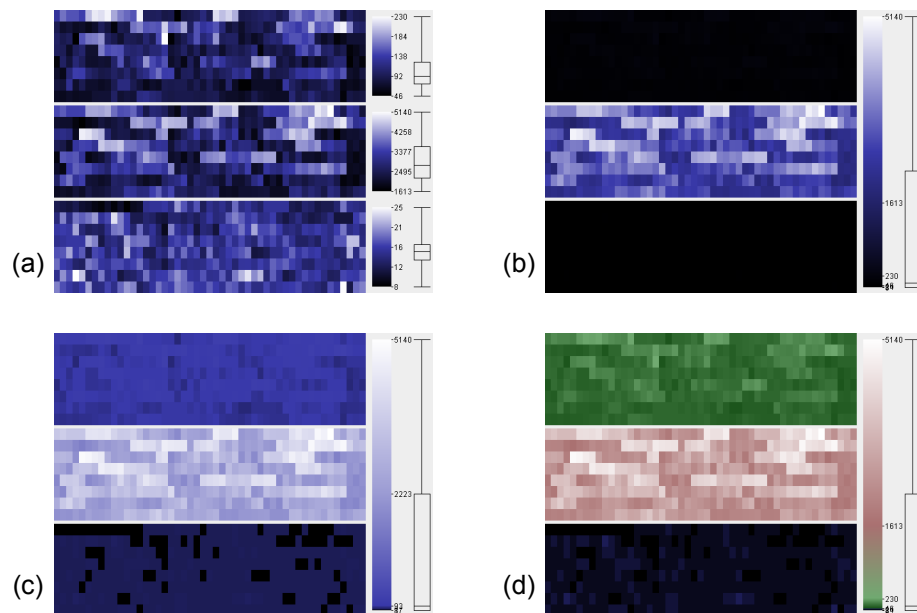


Figure 6: Visual comparison of three attributes. (a) Individual color scales; (b) one global color scale; (c) adapted color scale based on Box-Whisker plot; (d) optimized color scale for comparison tasks (also see Figure 5).

tative values only. However, many application fields require support for qualitative data as well. Future work will therefore concern the expansion of the proposed methods to cope with categorical data.

Last but not least, we need evaluation of the methods proposed here. We encourage perception and user study experts to formally evaluate our concepts, we will gladly provide our tools and support.

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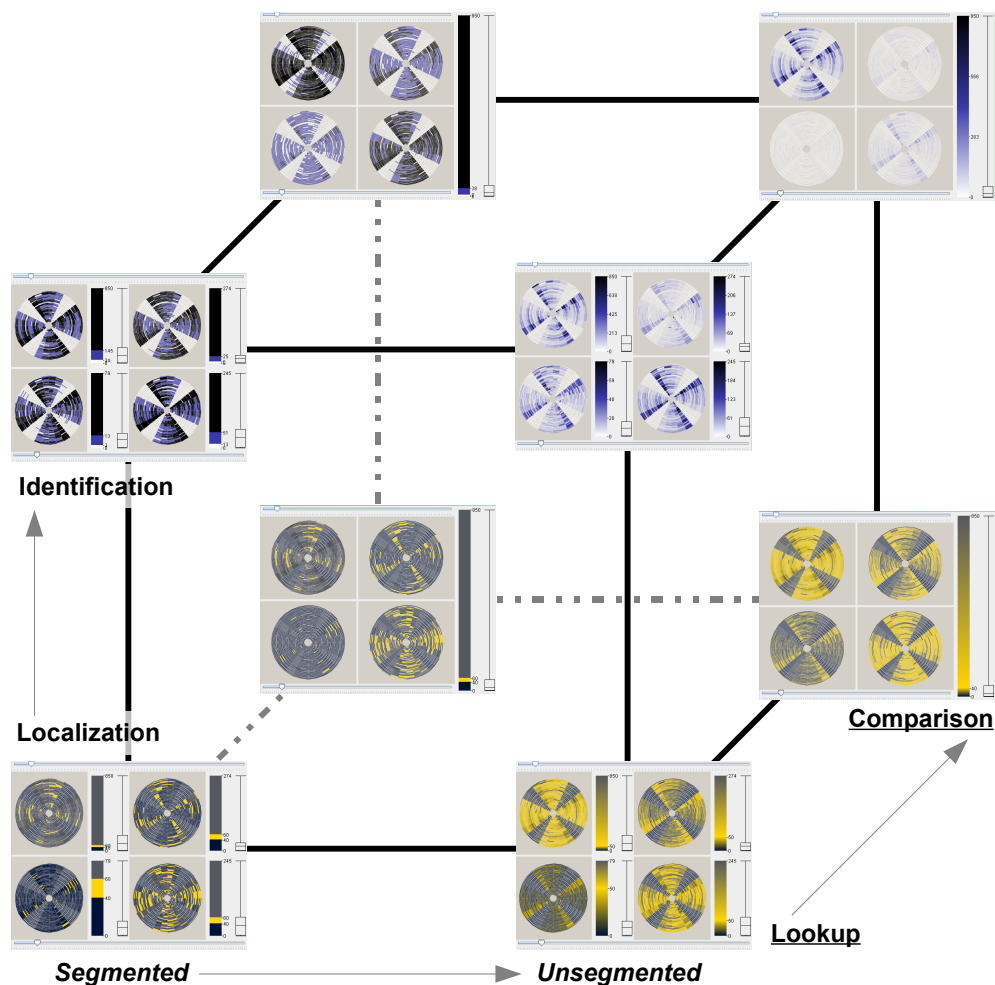


Figure 7: The task-color-cube. The cube spans along the axes segmented vs. unsegmented, identification vs. localization, and lookup vs. comparison. Each corner of the task-color-cube represents a specific task instance and is associated with a particular color coding scheme.

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