# Evaluating the Effectiveness and Efficiency of Visual Variables for Geographic Information Visualization

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**Abstract.** We propose an empirical, perception-based evaluation approach for assessing the effectiveness and efficiency of longstanding cartographic design principles applied to 2D map displays. The approach includes bottom-up visual saliency models that are compared with eye-movement data collected in human-subject experiments on map stimuli embedded in the so-called flicker paradigm. The proposed methods are applied to the assessment of four commonly used visual variables for designing 2D maps: size, color value, color hue, and orientation. The empirical results suggest that the visual variable size is the most efficient (fastest) and most effective (accurate) visual variable to detect change under flicker conditions. The visual variable orientation proved to be the least efficient and effective of the tested visual variables. These empirical results shed new light on the implied ranking of the visual variables that have been proposed over 40 years ago. With the presented approach we hope to provide cartographers, GIScientists and visualization designers a systematic assessment method to develop effective and efficient geovisualization displays.

**Keywords:** Geographic visualization, visual variables, eye movements, change blindness, empirical studies.

## 1 Introduction

The cartographic design process is about a systematic transformation of collected (typically multivariate) spatial data into a two-, three- or four-dimensional visuo-spatial display. This process is typically performed by applying scientific (i.e., systematic, transparent, and reproducible) cartographic design methods, as well as aesthetic expressivity. Principles and details of the map design process can be found in many of the well-established cartography textbooks (see for example Dent, 1999; Slocum et al., 2008). More recently, cartographers have not only been interested in "what looks good" or "what visually communicates well", but also increasingly how and why a particular design solution works well or not.

Although the seemingly intuitive design principles have been successfully used for hundreds of years, and some of them (e.g., "light is less–dark is more") have even

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been internationally accepted as conventions, for example, in the statistics community (Palsky, 1999), very few of the proposed conventions have actually been tested systematically for their effectiveness and efficiency with human users. One such example is the well-known system of the seven visual variables proposed initially by the French cartographer Jacques Bertin (1967; and translated to English in 1983) and later extended by various cartographers, see for example, Morrison (1974) and MacEachren (1995). More recently, Bertin's work has also received attention in the information visualization literature (Mackinlay, 1989). The variables seem to work when employed logically, but designers are typically not certain why. Unfortunately, there is very little empirical evidence on the effectiveness and efficiency of these visual variables (MacEachren, 1995). How can GIScientists, geovisualizers, and cartographers be sure that their design decisions produce effective and efficient displays? Naïve users tend to extract information based on perceptual salience rather than on thematic relevance (Lowe, 2003; Fabrikant & Goldsberry, 2005). For this reason, an empirical evaluation of design principles, and a systematic look into the relationships between perceptual salience and thematic relevance in visualization design is needed (MacEachren & Kraak, 2001) to understand how and why certain displays are more successful for spatial inference and decision making than others.

## 2 Related Work

### 2.1 Visual Variables for Guiding Visual Attention

Bertin (1967/83) proposed a systematical approach to communicating information by visual means. He lists seven basic visual variables and presents effects of varying the perceptual properties of the visual variables in order to derive meaningful representations. There are two planar variables (the x and y position on the map plane), and five so-called "retinal" ones (size, color value, color hue, shape, and orientation), which we (and perhaps vision researchers) would probably translate as "pre-attentive" (Bertin, 1967/83). Although Bertin (1967/83) lists these variables individually, effective map representations can of course include a combination of various visual variables (MacEachren, 1995).

Bertin distinguishes *selective*, *associative*, *ordered* and *quantitative* visual variables. A visual variable is *selective* (e.g., color hue) and therefore fundamental for symbolization of data, if all symbols can be easily isolated (perceptually selected) to form a group of *similar* symbols based on this variable (e.g., *where* are the red signs compared to the green signs). Bertin contends that shape (for points, lines and areas) and orientation (only when applied to areas) are not selective. Conversely, a visual variable is called *associative* (e.g., shape) if it allows to perceptually group all categories or instances of symbols based on that particular visual characteristic (signs of the same shape with different sizes vs. signs of different sizes with the same shape). Only the visual variables *size* and *color value* are said to have perceptual *dissociative* characteristics (Bertin, 1967/83). With dissociative visual variables (e.g., size) it is easier to detect visual variations among the signs themselves, than to visually form groups of similar symbols across other visual variables. Dissociative variables can be *ordered* or *quantitative*. A visual variable is defined *ordered* if it is possible to perceptually rank symbols based on one particular visually varying characteristic (e.g., lighter vs.

darker shading). If it is possible to perceptually quantify the degree of variation of a visual symbol, the visual variable property is defined as *quantitative* (e.g., size). Bertin furthermore ranks visual variables in an explicit sequence: higher order variables (e.g., size) which possess a greater number of perceptual characteristics (i.e., quantitative, ordered, and dissociative), compared to lower order variables (e.g., orientation), that may only have associative characteristics (only for areas).

Ironically, Bertin does not cite any perceptual or psychophysical work that would provide empirical evidence to his design guidelines. In fact, his seminal volume on the *Semiology of Graphics* (1967/83) does not include any reference to any previous or related work. Bertin's contributions can be understood within the context of the work by Gestalt psychologists such as, Wertheimer and Koffka in the 1920s (reviewed by Gregory, 1987 and Goldstein, 1989) who posited that the arrangement of features in an image plane will influence the perceived thematic or group membership relations of elements (i.e., figure/ground separation). Bertin's proposals have been somewhat supported by later experimental evidence for classic visual search tasks (e.g., pop-out vs. conjunctive search) proposed by Treisman and colleagues (e.g., Treisman & Gelade, 1980). In a meta study summarizing several decades of visual search and attention work in psychology and neuroscience, Wolfe & Horowitz (2004) list color (hue), size and orientation as undoubted variables to guide visual attention (for static displays), and color value (luminance) and shape as probable cases. Interestingly, these variables are not congruent with the ordering that Bertin suggests. Most if not all of this empirical work, however, has been performed on highly controlled, and therefore simple graphic displays, typically containing only simple and isolated geometrical signs, thus not complex graphics such as commonly used maps, or other kinds of visualizations.

Visual search strategies in a geographic context have been studied on realistic looking scenes such as maps (Lloyd, 1997), aerial photographs (Lloyd et al., 2002), and on remotely sensed images (Swienty et al., 2007). Additional empirical evidence for the validity of the visual variable system in more complex cartographic displays have been provided in the context of weather maps (Fabrikant et al., in press), thematic map animations (Fabrikant & Goldsberry, 2005), or for depicting the distance-similarity metaphor in information spatializations (Fabrikant et al., 2004; Fabrikant et al., 2006). Visual attention guiding variables have also been employed for the construction of computational vision models, as will be discussed in the next section.

## 2.2 Computational (Bottom Up) Models of Visual Attention

Itti & Koch (2001) present a computational framework to model visual saliency, based on based on neurobiological concepts of visual attention (Itti et al., 1998). The aim of the various computational models of visual attention is to model and predict visual attention based on psychophysical and neurophysiological empirical findings with human subjects (Koch, 2004). Visual saliency models also allow investigating complex and dynamic situations like animations, and changing natural scenes (Rosenholtz et al., 2007). Hence, they seem to be promising candidates for evaluating map displays as well.

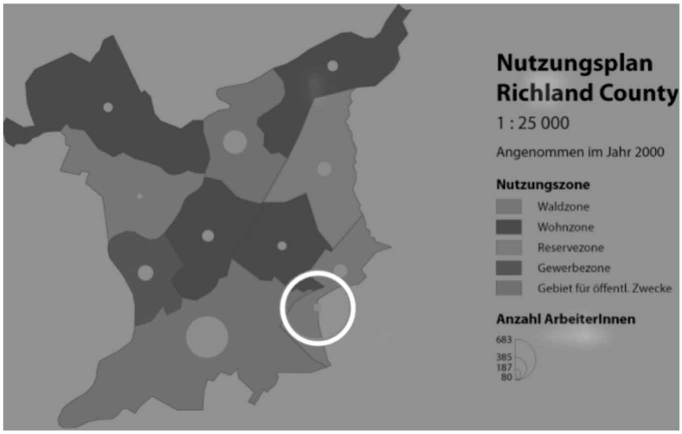


**Fig. 1.** Stimulus with predicted first eye fixation based on its saliency map

The Itti model is a neural-net based, neurobiologically plausible vision model. The goal of the model is to identify the focus of attention of a visual system (mammal or robot) based on the 'where' (e.g., perceptually salient characteristics), but not the 'what' (e.g., semantic characteristics, requiring cognition). In this model, three filters are applied to extract *color hue*, *color value* and *orientation* contrasts at several levels of image resolutions in a visual scene. Interestingly, these are three of Bertin's proposed visual variables. Three feature maps (one for each filter) are computed based on center-surround comparisons. Feature maps are additionally computed at several image resolutions and integrated to form a single conspicuity map for each feature type. A non-linear normalization is applied to each conspicuity map to amplify peaks of contrasts relative to noise in the background. In the final stage feature maps are combined to produce a single saliency map (SM). The saliency model also predicts a sequence of locations (ranked saliency peaks in the SM) that will attract a viewer's gaze in a scene (Parkhurst et al., 2002). The predicted initial eye fixation (white circle) is shown Figure 1. Lighter areas in Figure 1 identify image locations with higher saliency.

It is important to emphasize that the Itti saliency map does not reveal top-down components of visual attention. However, because we specifically employ a bottom-up approach within the flicker paradigm (see next section), and we are interested in evaluating the "retinal" (e.g., "pre-attentive") characteristics of map symbols, we contend this not to be a limitation for our study. Moreover, despite these limits, saliency map models appear to have already proven to be useful for cartographic purposes (Fabrikant & Goldsberry, 2005; Fabrikant et al., in press). We employ the visual attention model developed by Itti and colleagues (Itti et al., 1998) as a baseline to later compare human subject viewing behaviors collected with eye movement data. While visual variables are said to guide visual attention based on visual saliency, it is important to be aware of limitations or failures of the visual system, which we discuss in the next sections.

### 2.3 Failures in Visual Attention

Change blindness refers to a failure in the visual system in that observers often fail to detect even very salient and large changes in a scene when a blank field separates two alternating images. Change blindness is defined as *"the inability to notice changes that occur in clear view of the observer, even when these changes are large and the observer knows they will occur"* (Rensink, 2005: 76). According to Rensink (2005) change blindness occurs in different situations and under various conditions, thus it is a well-established phenomenon of human visual perception. Changes involving perceptually salient features are easier to detect than changes involving perceptually less salient features (Simons, 2000). As mentioned earlier, previous work has already demonstrated that visual attention and visual perception are tightly related (see review by Wolfe & Horowitz, 2004).

Rensink et al. (1997) introduced the flicker paradigm in order to investigate the phenomenon of change blindness. In the flicker paradigm *"an original image A repeatedly alternates with a modified image A', with brief blank fields placed between successive images"* (Rensink, 1997: 368).

Attention is characterized by bottom-up (stimulus-driven) and top-down (goal-driven) attentional control (Wright & Ward, 2008). The bottom-up component of attention is modeled in the flicker paradigm asking observers to detect the change as quickly as possible (Rensink, 2005). As a consequence, the memory impact on the experiment is reduced, but not completely inhibited (Rensink, 2005).

The dependent variable that can be measured under flicker conditions is the response time (Rensink, 2005). An observer is asked to solve three kinds of tasks: 1) change detection (what?), 2) change localization (where?), and 3) change identification (how?) (Rensink, 2002). Experimental results report that the identification task is typically the most complex task to handle (Rensink, 2002).

## 3 Experiment

In a controlled experiment we empirically investigated the relationships between the perceptual salience and thematic relevance in static 2D map displays. We employed a systematic bottom-up evaluation approach using the flicker paradigm (Rensink et al., 1997), in combination with the eye movement data collection method. In our experiment we focus specifically on those visual variables (i.e., size, color value, color hue and orientation) that according to Wolfe & Horowitz (2004) have been proven in psychophysical studies not only to guide visual attention, but are also used in a state-of-the-art visual saliency models (Itti et al., 1998).

In order to test the efficiency and effectiveness of these visual variables with users we prepared thirty-two thematic 2D map stimuli varying the visual variables size, color value, color hue and orientation (within-subject independent variables), embedded in a flicker display. The experiment consisted in solving three kinds of tasks: change detection, change localization, and change description. We hypothesize that the most efficient visual variable is detected *faster* in a flicker display than less efficient ones. Moreover, the more *effective* a visual variable, the more accurate participants' responses will be in a flicker display, compared to a less effective visual variable. To investigate these two hypotheses, the dependent variables *time of response* and *accuracy of response* are measured. In addition to the traditional success measures we additionally collect procedural data in the form of participants' eye movements when solving the experiment tasks. In this way, we hope to not only identify which visual variable works best, but also *how*. Finally, we derived saliency maps of the stimuli using a bottom-up computational model of visual attention (Itti et al., 1998). These saliency maps provide additional information about the saliency effects of the employed visual variables, and permit validation with the collected eye movement data.

**Participants:** Twenty participants (9 females and 11 males), recruited from the University of Zurich (UZH) and from the Swiss Federal Institute of Technology (ETH) Zurich, took voluntarily part in this study. They were not given any recompensation for participation. Participants were on average 29 years old, and no one indicated to be color-blind. Participants were selected to represent a range of professional backgrounds, without any experience regarding the flicker paradigm and its implications. On average the participant pool has a low to average training in geographic information science, such as cartography, geographical information systems, including the general familiarity with and usage of spatial data. Participants had a low or average level of training in computer science and related fields.

**Materials:** Sixty-four 2D map stimuli were designed in AdobeIllustrator and embedded in thirty-two flicker animations using AdobeFlash, according to the guidelines proposed by Rensink et al. (1997). The animations were embedded in a web page that could be automatically loaded by the eye tracker management software during the experiment. The flicker animations include four types of maps (i.e., eight flicker animations for each type) systematically varying the visual variables color *hue*, color *value*, *size*, and *orientation* (within-subject independent variables). To keep the map design consistent across trials, the stimuli included graudate circles and choropleths, as depicted in Figure 2 below. For the size stimuli, circle sizes changed, while the uniform area fills in the choropleth map was held constant. For the other three variables the area fills were affected by change, while the cirlces sizes were held constant. Fgure 2 shows a map stimulus used in the experiment.

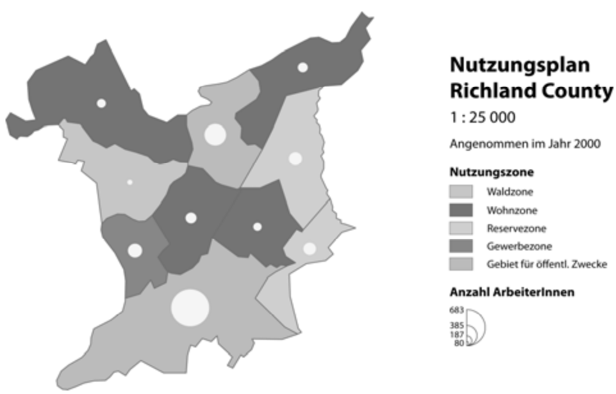


**Fig. 2.** Sample map stimulus evaluated in the study (color hue)

The maps in the flicker animation depict a set of randomly selected Swiss municipalities at a scale of 1:100,000. The geometry of the maps was systematically rotated in steps of forty-five degrees to assure that participants would not recognize the location, and therefore are able to focus their attention entirely on the change detection tasks. Based on the data characteristics (shown in the legend), we selected the appropriate visual variable for each thematic map stimulus, applying Bertin's (1967/83) design guidelines. Only the map portion of the graphic stimulus exhibits change between two consecutive displays. The change locations were also systematically varied so that areas in the center and various periphery locations in the map would change. Map title and legend never changed. An arbitrary map title was chosen by randomly selecting a county name in the U.S.A. (unknown to Swiss participants). The chosen name does not match the shown geometry. The legend includes a map scale (i.e., randomly selected representative fraction), a map symbol key, and respective attribute information. The maps do not contain any other map elements, such as author information, data source, or copyright sources. We reduced the design to a necessary (ecologically valid) minimum, in order to minimize cognitive load, and thus not further distract participants from the change detection tasks.[1]

**Setup:** The experiment took place in a windowless office, specifically designed and used to run eye movement experiments. It was administered on a Dell Precision 390 Windows workstation. The Tobii Studio software was employed to display the map stimuli and test questions on a 20-inch flat panel display, at 1024 by 768 pixels screen resolution. A standard mouse and keyboard were used for input. Participants' eye movements were recorded using a Tobii X120 eye tracker, at 60 Hz resolution. We employed a fixation filter with radius of 50 pixels, and minimal fixation duration at 100ms to collect participants' eye movements. Response time was measured as the elapsed time in milliseconds between the trial display appearing on the screen and the participant hitting a designated key on the keyboard to proceed to the next screen containing test questions.

**Procedure:** At the beginning of the test session participants were welcomed to the eye-tracking lab, signed a consent form, and filled out a background questionnaire. Participants were then asked to sit comfortably in front of the experiment computer connected to the eye tracker. Information on the testing procedure was displayed on the screen. Participants first performed two change detection trials to get comfortable with the test instrument, without having their eyes tracked. Following the practice trials participants' eye movements were calibrated with the eye tracker. Participants were again informed to sit comfortably, but as still as possible during the experiment, to improve calibration accuracy and consequently the eye tracking accuracy for the experiment.

For each flicker animation, participants were asked to hit the F10 key as soon as they saw a change. After the animation stopped and the stimulus disappeared, an answer screen appeared displaying a black and white reference map including area labels. Participants were asked to answer three questions. Firstly, if they had seen a

[1] Stimuli and experimental questions are available at: http://www.geo.uzh.ch/~sgarland/master/.

visual change (detection task); secondly, where they had seen the change (localization task); and finally, to describe the change (identification task). Participants responded to the test questions orally by refering to area labels on the reference map and the experiment leader recorded their answers using a digital microphone, and by typing responses into a digital file. After answering the three questions, participants launched the next flicker animation by hitting the F10 key. If participants did not see any change, the animation stopped automatically after 60 seconds. Participants were then asked to continue to the next trial by hitting the F10 key. The display order of the stimuli was randomized to avoid any potential learning bias. After completing the on-screen experiment participants were debriefed, and thanked for participation.

## 4 Results

Figure 3 shows participants' response times (efficiency) for the change detection task on the four tested visual variables. On average, participants took more time to detect a change in a map display varying the visual variable orientation (M=1.94s, SD=1.08s) compared to the other tested visual variables. The variable size yielded the shortest response time (M=0.65s, SD=0.21s), followed by color hue (M=0.92s, SD=0.73s) and color value (M=1.00s, SD=0.33s).

A repeated measures ANOVA (including a Bonferroni correction) reveals a significant overall effect for the (within-subject) "visual variables" factor, $F(25.805) = .000$, $p < .05$, indicating that there is a significant efficiency difference between the visual variables under study. Pairwise comparisons reveal that the variable orientation is indeed the least efficient visual variable for detecting a change. For maps containing this visual variable people take significantly longer to detect a change than for all other maps. Furthermore, while the variable size is the fastest of all tested visual variables, it is only significantly faster than orientation and color value. The speed advantage to color hue is not significant. There are no significant speed differences between color hue and color value.

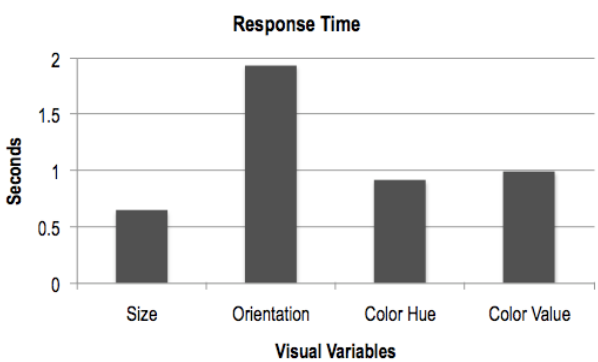


**Fig. 3.** Response time values in seconds

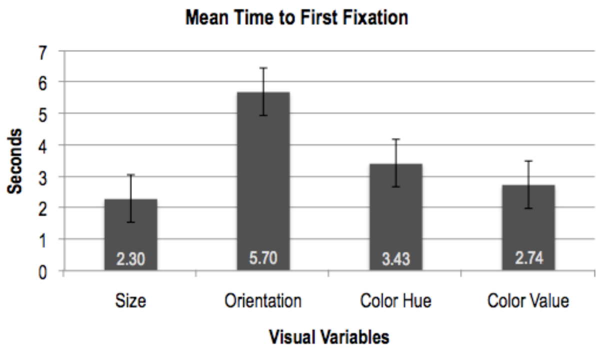


**Fig. 4.** Mean "*time to first fixation*"

We additionally investigated the efficiency (detection speed) of the visual variables by examining participants' eye movement behavior. For each stimulus, we delineated an area of interest (AOI) where a change occurs in the map. The efficiency metric *time to first fixation* (Goldberg & Kotval, 1999) can be employed to identify how long participants take to first fixate that particular AOI. This metric is negatively correlated with the potential degree of saliency of a region. High values of time to first fixation denote low degrees of saliency (Jacob & Karn, 2003). Figure 4 depicts the average length (in seconds), until participants fixated the relevant AOI for the first time during a trial. Again, people are slowest to first fixate on orientation changes, compared to color hue, color value, or size changes (fastest).

A repeated measures ANOVA reports a significant main effect for the four tested visual variables, $F(6.623) = .004$, $p < .05$. Size is significantly faster compared to orientation, but there are no significant differences between size and color hue or color value. Orientation is significantly slower than all the other tested variables, except compared to color hue. Size (fastest) and orientation (slowest) are at the extreme ends of the efficiency spectrum. There are no clear winners between color hue and color value.

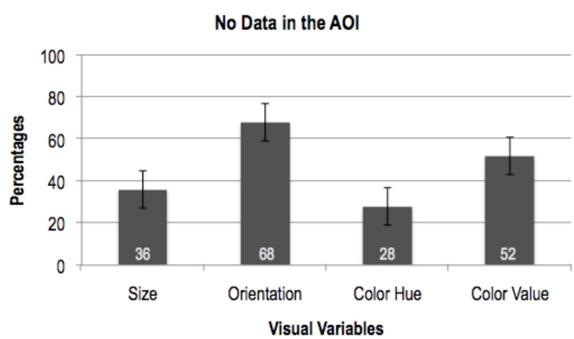


**Fig. 5.** Percentages of changes detected without looking explicitly at the change AOI

As Irwin (2004) notes, it is likely that the area of visual attention is larger than the location to where the fovea is pointing during a fixation. Evidence for this can be found in Figure 5. This Figure shows percentages of change that participants were able to detect correctly, without even fixating in the respective AOI. It is notable, that in 68% of the orientation trials (thus more than just by guessing) participants detected change without even fixating the respective "change" AOI. The percentages for the other trials are: color value (52%), size (36%) and color hue (28%), respectively.

To further look into the attention guiding potential or saliency of a visual variable we computed a ratio between the fixation duration within an AOI placed in the visual center of the map and the fixation duration within a "change" AOI. If this ratio provides lower values, observers' eyes were less attracted to the target AOI compared to "staring" into the center of the map. Higher ratio values might suggest that people's gazes moved around the map more or were attracted more readily to other attention guiding regions of the display. Size and color value (both 1.59) have the highest ratio, compared with orientation (1.29), and color hue (1.20). This measure qualitatively confirms the results depicted in Figure 4. Size and color value seem to have attracted participants gazes more than color hue and orientation.

We now turn to change localization. Regardless of the visual variable, people generally performed very well on the change localization tasks. This might be due to the stimuli having relatively low complexity. The size changes were localized practically error free (99%), followed by color hue and color value (both M=.994 SD=.028), and finally orientation with the lowest score (M=.925, SD=.143).

A repeated measures ANOVA for the change localization task provides evidence that there are significant differences among the visual variables, $F(7.589) = .002$, $p < .05$. Analog to the efficiency outcome for the change detection task, the variable orientation (least accurate localization) differs significantly from size (most accurate localization). No significant effects seem to exist between the other visual variables.

Figure 6 above also shows the percentage of correctly described types of changes. There is little difference in people's accuracy describing the change for size (99%), color hue (92%) and color value (97%) displays. However, changes in orientation seemed to have been much harder for people to describe accurately (69%).

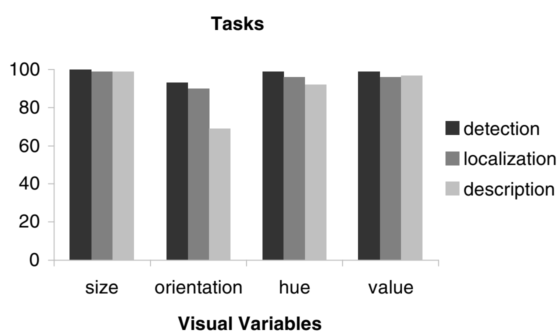


**Fig. 6.** Percentages of correct change detection, localization and description

According to a repeated measures ANOVA there seems to be a significant difference in the change description accuracy across the visual variables, $F(15.227) = .000$, $p < .05$. The variable orientation differs significantly from to the other three visual variables, yielding the least accurate results. Size scores are highest again, with 100% description accuracy; significantly better than color hue and orientation. Color value does not differ significantly from size and color hue.

### 4.1 Computational Saliency Evaluation

We additionally evaluated the animated flicker displays with previously mentioned Itti saliency maps, using specifically the saliency model for dynamic visual scenes. In addition to contrasts in color hue, color value and orientation (for static scenes), the dynamic model also takes movement variables into consideration to compute the resulting saliency map. The additional dynamic variables considered are: change in location (motion up/down/right/left) as well as flicker (i.e., appearance and disappearance at a location).

We compared the location of highest saliency computed by the model and its respective predicted eye fixation pattern with the actual change locations and our own collected eye movement data. The region of the change is indeed predicted by the model to be the most salient region in the saliency map. The model seems to work particularly well for the size displays. Comparing the predicted saliency maps of the map stimuli across the four tested variables, it is notable that the model yields a few highly concentrated areas of high saliency for the size stimuli, but less so for the other variables, where salient areas are more spread out and less crisp. On average, color hue has more salient locations in its saliency maps than the other tested variables. Consequently, one would expect that observers would be attracted to a larger number of locations competing for saliency (e.g., distractors), which might make the detection ("pop out") of a changing area more difficult. Based on this, one might further argue that the variable color hue would yield the worst results in a change detection task. However, our empirical results do not support this hypothesis. Participants had greater difficulty and took significantly longer to detect a change in an orientation map than for the other maps. Perhaps orientation maps do not provide enough visual contrast between the enumeration areas. The linear pattern of the zone boundaries is harder to isolate, due to the linear fill pattern within the zones. The individual enumeration units seem to form larger homogeneous regions with little figure-ground contrast. Henderson & Ferreira (2004) note that uniform regions are characterized by low fixation counts and consequently they do not draw visual attention. On average, orientation provided fewer fixation counts in the "change AOI" than the other three visual variables.

As we used animated graphic stimuli for the assessment of the visual variables, we need to also consider the effectiveness and efficiency of the visual variables for animated, or dynamic (e.g., interactive) visualizations. The overall advantage of size and (to a lesser extent) color value in the change description task can perhaps be explained by the additional influence of the dynamic variables (also computed for the saliency map). Figures 7-8 show samples of overall saliency maps for the four tested visual variables, overlaid on top of a map stimulus (upper left panel). The lighter the shade ("spot light") the higher the saliency. The white circle in the map stimulus is the predicted first gaze point (location of highest saliency). All the saliency attributes contributing to the overall saliency map are placed to the right and below of the map stimulus (panels with black background). Both size (Figure 7a) and color value (Figure 8b) yield areas of high saliency that are highly localized, compact, of small extent, and with crisp boundaries (especially for the size variable). This is perhaps due to optimal correlation of the visual variables (hue, value and orientation) with the dynamic ones such as, flicker (on/off) and motion (left, down, up, and right). The hue maps (Figure 8a) and orientation maps (Figure 7b), showing a much more dispersed pattern in their saliency maps, for both the static (visual) and dynamic variables, seem to be less effective at guiding people's attention to the relevant areas of change.

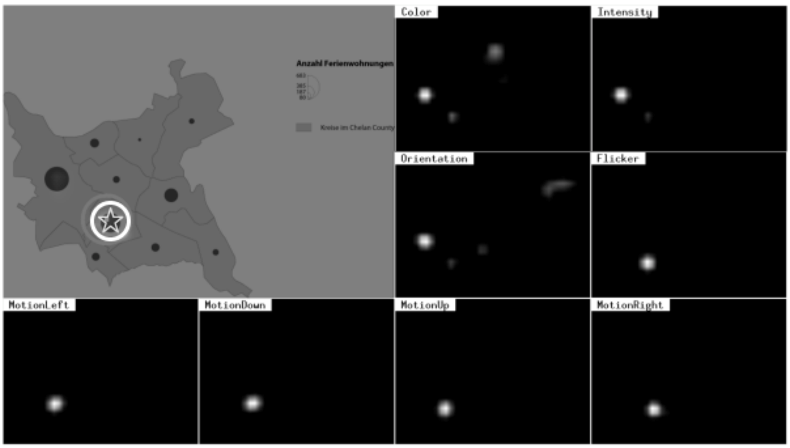


**Fig. 7.** Saliency maps for the visual variable size

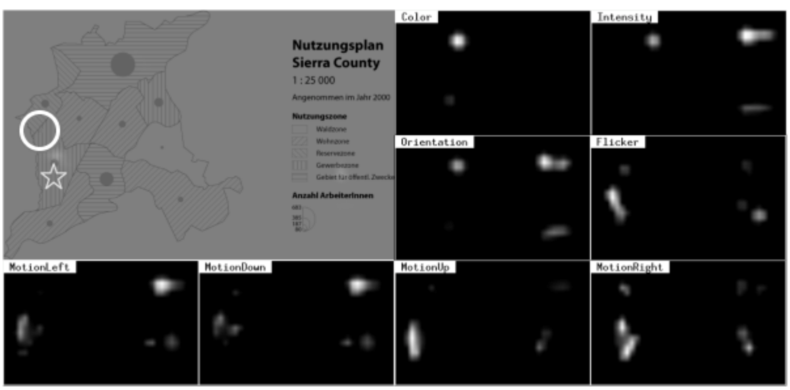


**Fig. 8.** Saliency map for the visual variable orientation

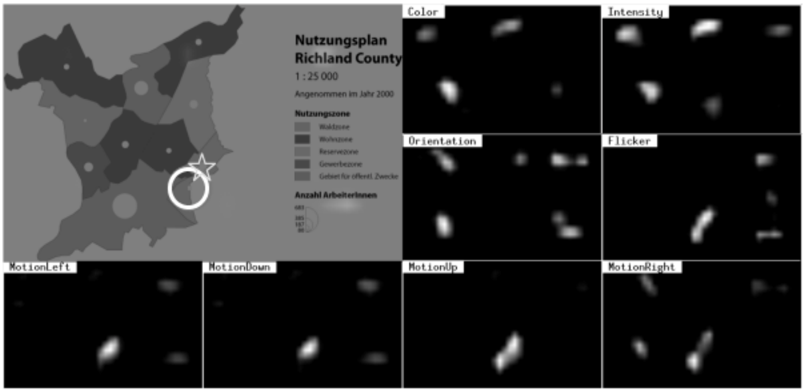


**Fig. 9.** Saliency map for the visual variable color hue

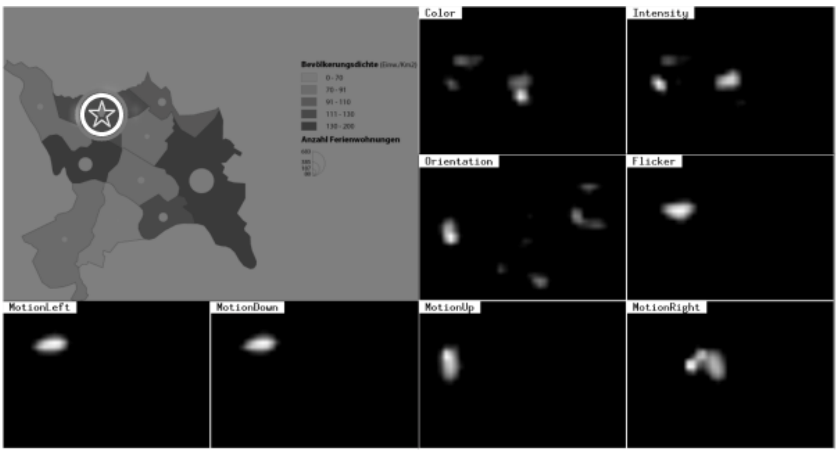


**Fig. 10.** Saliency map for the visual variable color value

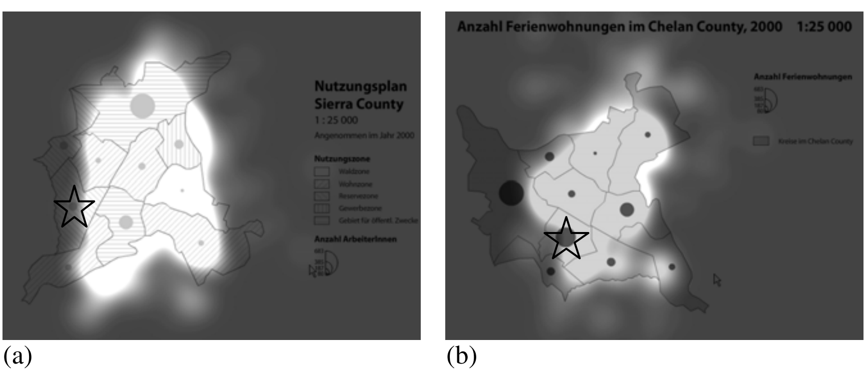


**Fig. 11.** Fixation concentrations across all participants for (a) orientation and (b) size

We now contrast (predicted) model results with our collected eye movement data. Figure 9 depicts two sample stimuli with aggregated eye fixations of all our participants. The lighter the display the higher the fixation concentration and magnitude.

It is striking (but somewhat counter intuitive) that the model correctly predicts (as shown in Figure 7b), and confirmed by our empirical data (Figure 9), that the largest of the graduated circles in the size display is attended the least. Both the center of the map and the smallest symbols receive most attention in the size display. It seems that (center-surround) contrast changes (modeled explicitly in the saliency maps) are indeed attention guiding. The smaller circles offer more "contrast-changes" against a homogeneous background than larger circles. Interestingly, only a small portion of the relevant change AOI (marked with a star symbol in Figure 9) was fixated in the orientation stimulus (compare with Figure 7b). This might be explained by the corner of the AOI being closest to the center of the map. Furthermore, if center-surround contrasts are relevant, then the concentration of stable boundary lines converging in a corner offer perhaps more contrast opportunities compared to directional changes of a linear fill pattern.

Overall, the model results and empirical result are very encouraging for cartographers, because they suggest that commonly employed visual variables, when correctly applied, are indeed able to effectively and efficiently guide observers' attention to relevant information. As Lowe (2003) suggests, congruently displaying thematically relevant information in a perceptually salient manner is one of the key challenges for designing effective and efficient map displays. However, empirical results presented in Figures 5 and 9, also provide some evidence that foveal attention and saliency are not always located in the same location.

## 5 Discussion

Summarizing our results we find that the selected four tested visual variables (Bertin, 1967/83) are indeed attention guiding, as people performed significantly above chance (e.g., 50%) in detecting, localizing and describing a change in the display. This is in accordance to the summary of results presented in Wolfe & Horowitz (2004)'s meta study on attention guiding attributes. These authors list color, motion, orientation, and size as "undoubted attributes" to guide visual attention. However, unlike Bertin (1967/83), Wolfe & Horowitz (2004) do not provide a ranking of the attributes. Our empirical results do provide some evidence for the implied ordering of Bertin's visual variables. We find the visual variable size to be the most efficient and effective variable to guide viewers' attention in thematic 2D maps, under flicker conditions. Perhaps this can be explained by the size displays being visually the least complex (e.g., having fewer visual distractors), according to the computational saliency model shown in Figure 7. According to Bertin, size is the only visual variable that has quantitative, ordered, selective (the signs perceived as different), and dissasociative characteristics (the signs are perceived as not similar). In fact, Bertin attributes size most "dissassociativeness". Since size emphasizes sign *difference* (e.g., change), one might argue from an information theoretic encoding perspective that difference or change could be an aspect of "interestingness", and thus, a very useful quality to guide attention. Since early eye movement studies on visual displays (Buswell, 1935;

Yarbus, 1967), it has been known that people concentrate their fixations on *interesting* and *informative* scene regions (Henderson & Ferreira, 2004).

The visual variable orientation appeared to be least effective and efficient of the four tested visual variables. As Bertin (1983: 93) writes: “in *area representation* variation in orientation is the easiest to construct, but it is at the same time the least selective” [of all seven visual variables]. Bertin assigns orientation only one attention guiding characteristic (i.e., associativity). He argues that with orientation (in areas) it is harder to isolate an area of change, as the variable emphasizes similarity, thus has a more uniform or homogeneous appearance. The computed saliency maps and our collected gaze data seem to support this idea.

For the color value and color hue variables the result pattern is not as clear. While color hue and color value yielded similar results, color value seems to have a slight (but non significant) advantage. In Bertin’s system, color value differs from size only in the lack of a quantitative characteristic, thus one would have expected color value to perform better than hue for change detection. These results might support Wolfe & Horowitz (2004)’s questioning of luminance polarity (e.g., contrast in brightness or color value) as an attention-guiding attribute. They suggest it might be a subset of color, that is, the luminance axis of a three-dimensional color space.

## 6 Conclusion

This paper presents a systematic empirical evaluation approach to assess the effectiveness and efficiency of four commonly employed visual variables (size, color value, color hue and orientation) for the design of 2D map displays (Bertin, 1967/83). The proposed evaluation approach combines the application of visual saliency models developed in research on human vision with the assessment of change under flicker conditions by combining traditional performance measures (accuracy and speed) with eye movement recordings. We find that the visual variable size performs most effectively (accurately) and most efficiently (fastest) under flicker conditions. Conversely, the visual variable orientation seems to be least effective and efficient in our change detection experiment. For color hue and color value the results pattern are not as clear. Our results suggest validity to the implied ordering of the visual variables proposed by cartographer Jacques Bertin (1967/83) over 40 years ago. This study also shows that both the saliency map approach and the measurement of eye fixations under flicker conditions can be employed to systematically assess the utility of Bertin’s (1967/83) system of seven visual variables widely used in cartography, and also discovered in information visualization (Mackinlay, 1989). The visual variable system was developed specifically to help cartographers better control the visual salience of symbols on maps. However, until today it lacked in systematical validation procedures, which we hope to have provided with this contribution.

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