Modeling Perceptual Dominance Among Visual Cues in Multilayered Icon-based Scientific Visualizations

Daniel Acevedo Jian Chen David H. Laidlaw

Department of Computer Science, Brown University – {daf, jchen, dhl}@cs.brown.edu

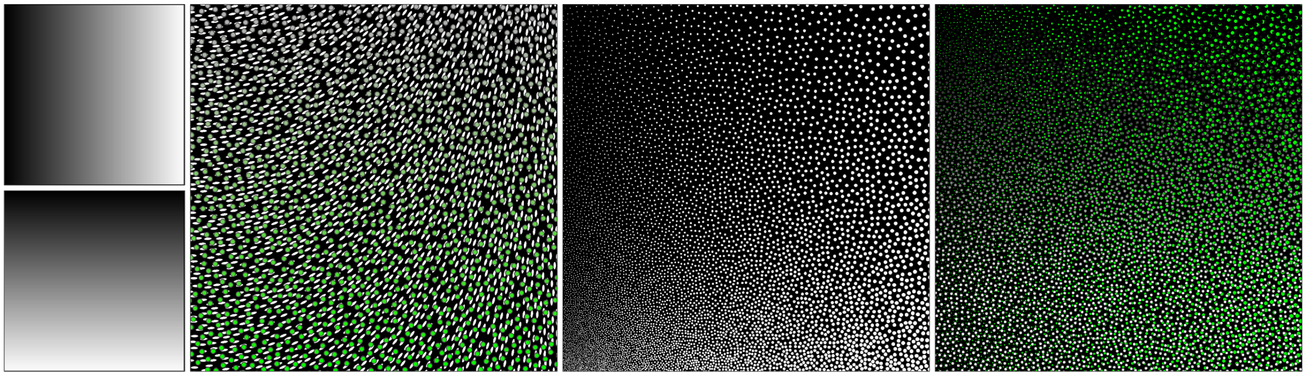

Figure 1: We present an experimental quantification of how factors such as icon size, spacing, layer order and color affect the relative saliency and interference among five different 2D scalar visualization methods: saturation, lightness, orientation, size, and spacing.(a) Two linear scalar fields used in the experiment. Images (b)-(d) are examples of the stimuli presented in the study: they all represent both linear fields simultaneously, and participants were asked to judge which one they perceived first, i.e. which one is the more salient of the two. (b) Icon orientation on the bottom layer and saturation on the top, (c) a single-layer example with size and spacing, (d) another two-layer display with size on the bottom and lightness on top. Top-layer icons have a gray-valued border at half the lightness value of the inside circle, so as to minimizes simultaneous contrast issues. Circles are used for all methods except orientation, which uses ellipses.

1 Definitions and Contribution

We define saliency as the perceived dominance of some visualization method over another when representing scientific data. This means that perception and correct understanding of the data must be assessed, not just the realization that some property of the icons is changing across the display (which a preattentiveness analysis would asses.) For example, orientation changes are very preattentive. Yet, as we will see, reading a scalar field from changes in icon orientation is very difficult, making it, in our definition, not very salient with respect to other methods. We measure saliency as the difference in time that participants take to recognize each of the datasets in our stimuli (see Figure 1). Saliency can be used to visualize the importance of some variables over others: designers may want some variables to dominate the composition while others should recede to the background.

Our experiment also recovers the perceptual interference among methods, which we define as the amount of distraction a method creates when users are trying to read another method present in the same display. We define these interferences as the time participants take to recognize each method while the distractor method is simultaneously changed and all other factors of the final display are controlled.

Our main contribution is a set of predictive models that, given a particular combination of methods, approximates the expected perceptual interference among them and the saliency level of the combination. This is a useful tool in generating effective visualizations based on the perceptual characteristics of the methods involved. Furthermore, with the derivatives of these models, we can confidently guide the user towards higher or lower saliency and interference by changing some or all of the factors involved. The search for an effective solution can even include and optimization process that weights the various factors involved.

2 Scope

One goal of visualization researchers is to maximize the bandwidth of information successfully transmitted by a visualization, while leveraging human competencies to understand its visual depiction. In other words, we want to optimize visualization creation by utilizing human visual resources efficiently. To achieve this we need to quantify and model how human perception explores the types of stimuli present in scientific visualizations.

A *visualization method* is an abstract function that transforms a scientific dataset into a visual representation to facilitate data exploration. In turn, a *visualization display* is the visual instantiation of a method. Here, we are interested in studying visualization methods for multivalued continuous scalar datasets in 2D, using multilayered icon-based methods. Furthermore, the goal of our visualizations is exploratory. We assume our end users want all the data displayed in an unbiased way: they have no preconceptions about more or less interesting areas that should be highlighted or blurred. In the multivalued case, their exploration seeks to understand the relationships among data values.

3 Experimental Methodology

Our experimental methodology is inspired by psychophysical studies on visual search and cue interaction [1,2]. We developed an experiment in which the stimuli resemble real visualization displays, which are notably difficult to evaluate perceptually. While still effectively controlling the experimental factors, this methodology allows us to generalize our results, and our predictive model, to real applications with complex multivalued datasets.

In order to control the saliency of a method we use a set of *knobs* that we will call our *visual dimensions*. Here, we analyze and model how the independent variables icon size, spacing, color, and layer order affect the saliency of five scalar visualization methods: icon saturation, lightness, orientation, size, and spacing. The independent variables are not tied to data and remain constant across the display, while data variables are mapped to methods.

We measure saliency through a visual-attention experiment. Using displays that show a two-valued scalar dataset (see Figure 1) and measuring the time participants take to recognize each of the values, we obtain a model of saliency in terms of how much the two times differ.

We presented our stimuli on a 1280x1024 CRT monitor. Visualization displays were images of 900x900 pixels on a black back-

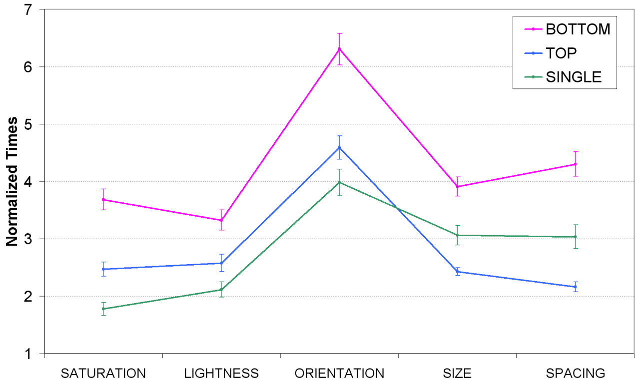

Figure 2: Mean normalized times and standard errors for one- and two-layer cases. Within each method, all differences are significant ($p < 0.05$). Orientation times are also significantly longer than all other methods for each case.

ground. The illumination of the room was kept low to avoid distraction when the changing images flashed on the screen, and we gamma-corrected both brightness and saturation ranges for approximate visual linearity. We used circular icons for all our methods. Size levels were fixed at 2, 6, and 10 pixels in diameter, and spacing levels (the distance between icons) were fixed at 0, 5, and 10 pixels. These values were chosen to obtain a characterization of method saliency with sufficient spatial feature resolution and data resolution[3].

We presented the experimental task as a question to the participants: "Which of the two linear gradients do you perceive and understand first? Once you understand one of the gradients, hit a key (H or V) to indicate whether it is the horizontal or the vertical gradient. After that, continue exploring the image until you either understand the second gradient, in which case you hit the other key, or the image times out after 10 seconds". A one-second distractor image was placed between stimuli so as to minimize carry-over effects from the previous choice.

We perform a full factorial design for all factors in the one-layer cases, and for the two-layer cases, we use a blocked randomized fractional factorial design using an orthogonal array[4] for the size and spacing factors of both layers. This is still a balanced design, since each level of each of the variables occurs equally often. For all other independent variables we used a full factorial. A total of six paid participants ran through the experiment, taking approximately one hour to complete the study with short breaks between sections.

4 Results

As is clear from the normalized time results for each method in Figure 2, mean times to recognize orientation as a scalar field are significantly higher than the rest. All participants declared difficulty understanding orientation as a scalar value. The pseudo-flow effect was so distracting as to prevent them from understanding the linear scalar datasets. For this reason, all further analyses of the experimental data exclude orientation cases. Interesting to note is how size and spacing methods are recognized faster when they are on the top layer of two-layer cases than for single-layer cases. This confirms the known preattentive precedence of the other three methods over these two for the single-layer cases.

Given the distributions of timing data for the two key presses for each pair, we obtain the following saliency measures based on the time differences:

- *Relative Saliency,* $S(v_i, v_j) \in (-1, 1)$: Here v_i and v_j are two of our visualization methods. $S = -1$ indicates that v_i is much more salient than v_j, and $S = 1$ indicates the opposite. Differences are normalized with respect to the maximum and minimum observed time differences throughout the experiment.
- *Interference,* $I(v_i|v_j) \in (0, 1)$: This measures how much v_j interferes with the reading of v_i. To measure this, we set $I(v_i|v_j) = \frac{T(v_i|v_j) - min(T(v_i))}{max(T(v_i)) - min(T(v_i))}$, where $T(x)$ is the time participants took to recognize method x. To obtain the extreme values we must look across blocks for all instances where v_i was presented. We assume that the minimum time is how long a participant would take to recognize a dataset using v_i when presented by itself.

With these definitions we tried to generate models for each pair, with separate models for the single- and two-layer cases. For example, for the two-layer case for the pair *saturation-lightness* (t, l), we obtained the expected normalized time difference $D(t, l)$ and the relative saliency $S(t, l)$:

$$D(t,l) = -7.2 + 1.1p_t - 0.1p_t^2 + 1.8s_l - 0.1s_l^2 - 1.7p_l + 0.2p_l^2 - 2.4r$$

$$S(t,l) = \frac{|D(t,l)| - min(D)}{max(D) - min(D)} \times \frac{D(t,l)}{|D(t,l)|}$$

Where p is spacing in pixels, s is size in pixels, and $r \in \{0, 1\}$ indicates whether the saturation layer is on top ($r = 1$) or not ($r = 0$). This model significantly captures the variance from our experimental data ($R^2 = 0.64$, $F = 38.2$, $p < 0.0001$), and we have obtained similar models, with comparable R^2 and (F, p) values, for all other pairs. For interference, we model the times to recognize each method for each pair, as opposed to the difference. For the same pair as before, the expected time to recognize lightness $T(l|t)$ and the expected interference of saturation over lightness $I(l|t)$ are:

$$\begin{aligned} T(l|t) = {} & 10.9 - 0.3s_t - 0.8p_t + 0.03p_t^2 - 1.3s_l \\ & + 0.1s_l^2 + 1.0p_l - 0.1p_l^2 + 1.0r \end{aligned}$$

$$I(t,l) = \frac{T(t,l) - min(T)}{max(T) - min(T)}$$

This model also fits the variance well ($R^2 = 0.61$, $F = 29.5$, $p < 0.0001$). We did not find models for the single-layer cases that would fit the data well. We believe the experiment is not powerful enough for those cases, since the number of single-layer stimuli is significantly smaller than the two-layer cases. We are running more participants to solve this issue.

It is important to note that the relationships among parameters and their meaning are the main contributions of these models, more than the exact coefficients. These were experimentally found through our analysis of the study results, but we are currently evaluating the hypothesis that these models apply in practical situations with more general datasets. A preliminary study using expert visual designers confirmed the models accurately predict expected saliency and interference, although a scale factor might be required based on the particular characteristics of the datasets depicted, such as value ranges and spatial feature sizes.

5 Conclusion

Our experimental data let us generate a set of predictive models that can be used to design effective visualization methods tailored to particular design goals. We can now confidently modify the parameters of our visualization methods to increase or decrease saliency and interference among them. We have also described some methodologies for gathering and combining the perceptual knowledge needed to create such models. We hope our success encourages further research in this field to create a full model of the space of visualizations.

6 References

[1] Callaghan. Dimensional Interaction of Hue and Brightness in Preattentive Field Segregation. Percep.&Psych., 36(1), 1984.

[2] Bergen et al. Computational Modeling of Visual Texture Segregation, in *Comp. Models of Visual Processing*, 1991.

[3] Acevedo et al. Subjective Quant. of Perceptual Interactions Among Some 2D SciVis Methods, TVCG, 12(5), 2006.

[4] Heydayat et al. Orthogonal Arrays: Theory and Applications, 1999.