Data multiplexing through animated texture orientation and color

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Keywords: Information Visualization, Multivariate Visualization, Animated Representations.

Abstract: Multidimensional data visualization is still a challenge for complex data exploration. Usually, each data dimension might be mapped to one available visual variable such as position, shape or color. While spatial and color data mappings have been previously intensively explored, animated encodings have been far less investigated. However, such techniques are widely used in existing visualizations. In this paper, we propose to assess the visual assets of direction and orientation of directed animated textures to encode data. We present a user study that compares three animated textures and a static representation. The results suggest that the animated techniques can be as effective as the static representation in terms of accuracy and data retrieval time. Finally, we present some design guidelines to efficiently use animated particle visualizations .

1 INTRODUCTION

Minard's visualization of Napoleon's march shows one of the most relevant data representation where multiple data dimensions are presented at the same time. Such an astute image is difficult to generalize and multidimensional data visualization is still today a challenge. If we consider a 2D surface composed of two axes (i.e. a screen), it offers two available data mappings (X and Y coordinate system which can be mapped to two data dimensions). In addition, other data dimensions can be mapped with other available visual variables such as size, color, and shape (Berlin and Barbut, 1968). These visual variables can also be animated across time to depict dynamic phenomena, as in some cartographic applications (DiBiase et al., 1992; Lobo et al., 2018). However, while spatial and color data mappings perception have previously been intensively explored, the perception of animated visualizations have been far less investigated.

This is especially the case with techniques using directional animated particles (Wegenkittl et al., 1997; van Wijk, 2002; Scheepens et al., 2016). These techniques are widely used in many engaging and pleasing animations to display flow information. For example, global wind visualizations (https://earth.nullschool.net/, https://www.windy.com/) show color streams that represent the strength and direction of the wind. Other types of visualizations use a color scale to display temperature data on top of the stream visualization (https://www.ventusky.com/). The TV show from the BBC, "Britain from above" (https://www.bbc.co.uk/programmes/b00d23yx) shows many instances of animated flows with various designs. Some examples are depicted in Figure 1.

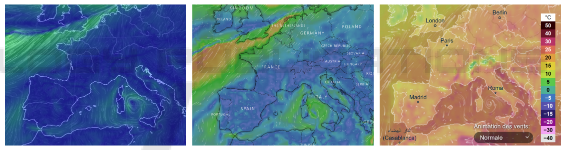


Figure 1: Example animated particle system to show flow directions.(https://earth.nullschool.net/, https://www.windy.com/, https://www.ventusky.com/).

All of these techniques offer the capability to visually represent two data dimensions. First, the direction of the flow codes one data dimension. Second, the color of the flow or the background codes another data dimension (i.e. stream intensity). While these techniques are currently used in many applications and research domains, we still do not know how efficient at representing these two dimensions simultaneously the different representation techniques are.

In this paper, we propose to assess the visual assets of such techniques. We conducted a user study where we show colored animated particles to visually map two data dimensions. The results suggest that techniques based on animated textures can perform as well as a static data representation in terms of accuracy and data retrieval time. Furthermore, we show that the orientation difference has an influence on the color retrieval. Finally, we summarize our findings with design guidelines to efficiently use animated particle visualizations.

2 RELATED WORK

2.1 Textures for Multivariate Visualizations

The use of textures for multivariate visualization has been explored through different techniques such as brush strokes (Kirby et al., 1999), quantitative textons (Ware, 2009), contour maps (van Wijk and Telea, 2001) and more recently decal maps (Rocha et al., 2017). Other techniques, such as the circular dataimage (Morphet and Symanzik, 2010) focus specifically in displaying angles. These techniques seem to be effective to depict multiple data attributes for a region, as textures enable to separate different scalar values. For example, Ware (2009) compares quantitative textons to bivariate color maps, and find they produce lower error rates when reading values.

However, all these studies focus on static techniques, and do not explore animated techniques. Furthermore, they compare techniques that are very different from each other, whereas in this study we aim at comparing only techniques that depict color and orientation

2.2 Textured-based Flow Visualization

The field of flow visualization has a long history of using animated textures to visualize flow characteristics. Flow visualization techniques are categorized as *direct, texture-based*, *geometric*, and *feature-based* (Laramee et al., 2003; McLoughlin et al., 2013). We review the most relevant existing work to our study on texture-based flow visualization techniques. For a more detailed review, we refer the readers to the surveys presented in (Laramee et al., 2003; McLoughlin et al., 2013).

Laramee et al. (2003) classify texture-based techniques as *Spot Noise Techniques*, *LIC techniques*, *Texture advection and GPU-based techniques*. LIC techniques apply a convolution to a noise texture that follows the direction of the vector field, resulting in a dense visualization. *Texture advection and GPU-based techniques* distort existing textures along the direction of the vector field using a predefined mesh. These techniques can be further extended to display multivariate data through weaving (Urness et al., 2003), contrast variation (Sanna et al., 2002) or variations of the initial noise textures (Kiu and Banks, 1996). Several variations and optimizations of these techniques exist (Stalling and Hege, 1995; Wegenkittl et al., 1997; Laramee et al., 2003) and it is now possible to achieve efficient rendering. However, it is still unclear how these different techniques are perceived and which one might be more efficient to understand the characteristics of the depicted flow such as its orientation and direction.

2.3 User Studies

Existing studies (Laidlaw et al., 2005; Moorhead et al., 2012) comparing static flow visualization techniques suggest that the more visually explicit methods (showing integral curves, critical points, and flow directionality) are more effective. Ware et al (2016) compare animated to static representations to visualize steady flow patterns. The results suggest that animated streamlets are faster and more accurate than static arrow grids, static streamlets and animated orthogonal particles for a pattern detection task. These studies only consider the flow representation through animated textures, but do not evaluate the simultaneous readability of flow animated direction and color. Ware et al. (2013) present new designs for a multivariate weather display, and evaluate their readability in a user study. Their results suggest that a map that combines animated particles, color and texture can be more readable than the traditional design that uses a static depiction. Their results suggest that users can read multiple variables on a weather display, but they only evaluate one technique of animated particles.

Our study aims at comparing animated texture-based flow visualization techniques to a static representation in both color and direction encoding. As opposed to the existing studies, we do not focus specifically on flow data and rather try to evaluate which technique is better to represent color and orientation simultaneously.

3 TECHNIQUES

We chose our techniques by reviewing the existing literature and visualizations used in websites. We tuned each technique iteratively to achieve the rendering that enabled us to depict the biggest range of orientation and color values.

3.1 IBFV

Image Based Flow Visualization (van Wijk, 2002) is a technique for visualizing flows. It is based on image wrapping and blending. For each frame, a white noise image is wrapped in the direction of the flow and then blended with another white noise image, as depicted in Figure 2. We implemented IBFV as described in (van Wijk, 2002). We rendered 60 frames per second and used a pattern resolution of 128 pixels with a speed of 110 pixels per second.

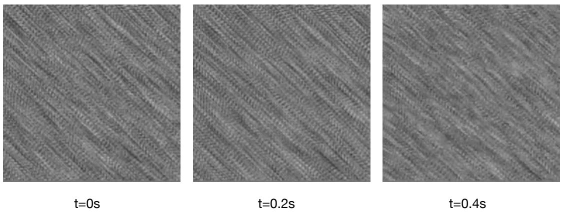


Figure 2: Example of IBFV animation depicting 40 degrees.

3.2 OLIC

Oriented Line Integral Convolution (Wegenkittl et al., 1997) encodes both direction and orientation, by distributing some random droplets and using a ramp-like convolution kernel, as depicted in Figure 3. This results in droplets that present a lighter color in the direction of the flow. If animated, each lighter point will move in the flow direction. This technique is the most used on existing web visualizations. We implemented OLIC as described in (Wegenkittl et al., 1997), but to make it more efficient, we pre-calculate the images corresponding to a complete phase shift of the kernel. We use droplets of length 20 pixels and a speed of 40 pixels per second, meaning that each droplet will be animated twice every second.

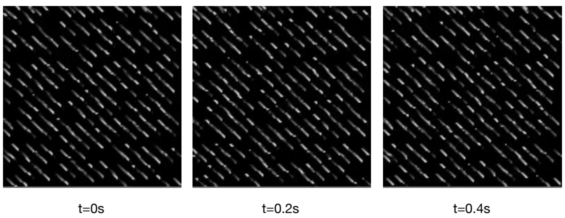


Figure 3: Example of OLIC animation depicting 40 degrees.

3.3 Drifting Texture

As we would use only linear speeds (to represent angle and direction) we also added a technique that scrolls across a static texture, that does not depict neither orientation nor direction statically, and only uses dynamics. Figure 4 depicts three frames of a drifting texture animation. For this technique, we used a speed of 20 pixels per second and a white noise texture.

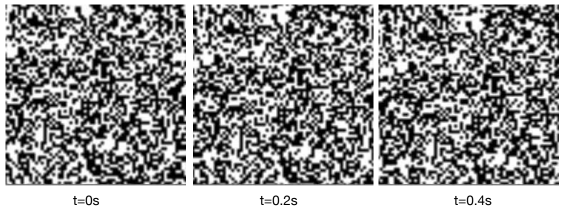


Figure 4: Example of DT animation depicting 40 degrees.

3.4 Static Representation

Previous studies suggest that animation might not be always beneficial (Tversky et al., 2002). Thus we added a technique that depicts both orientation and direction statically as the baseline. This technique does not distort colors in any way. We chose to use an arrow field, as arrows are commonly used to encode direction (Ware et al., 2016), and they are always completely opaque, so they do not introduce any interference with the color we want to represent, as depicted in Figure 5.

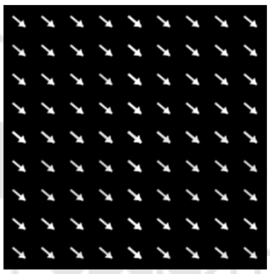


Figure 5: Example of STATIC depicting 40 degrees.

4 USER STUDY

Several studies attempt to understand which color scale is better for data visualization such as the Color Brewer tool (Harrower and Brewer, 2003) that helps mapmakers choose the most suitable color scale to their data. Our design study is inspired by the more recent study presented by Liu et al. (2018). In it, participants were asked to compare color distance, by choosing the closest color among two options to a reference color. Their results suggest that multi-hue color scales perform better than single-hue color scales and they find that the recent color scale *Viridis* perform especially well.

Our study uses the same structure, but besides asking participants to compare colors, we asked them to compare orientations. In each trial, participants are asked to choose the closest value among two alternatives to a reference value. We use the same methodology to select the reference colors that the one presented by Liu et al. (2018), we consider that the color scale spans from 0 to 100 and choose 8 equally spaced color values from 20 to 80. For the angles, we use 36 equally spaced angles between 0 and 360. The two other values are then selected according to spans as in (Liu and Heer, 2018). For example, if we use a span of 20, the closest value will be at a difference of 5 of the reference and the farthest at a difference of 10. Then, if the reference value is 20, the comparison values will be either 15 and 30 or 10 and 25. A pretest with two color spans and three angle spans resulted in a too long study and as the study presented by (Liu and Heer, 2018) already studies the color comparison, we decided to only vary the angle span. Therefore, we always use a color span of 15 and three different ANGLE SPAN values: 15, 30, and 45. We chose to not use smaller ANGLE SPAN values because humans performance when comparing angles is poor (Cleveland and McGill, 1985). Furthermore, following the suggestions presented by the results of the study, we chose to use the *Viridis* color scale, displayed in the bottom of Figure 7.

As the goal of this techniques is to represent multiple data dimensions in visualizations that have also space constraints, such as heat maps, we wanted to also study the impact of the size of the animated region on the color and orientation perception for each technique. So, our user study also considers three values for the size of the animated patches.

4.1 Hypothesis

We propose a characterization of the techniques according to the information they encode in their graphic depiction, if they encode information dynamically and their color density, depicted in Figure 6. Considering this, we draw two main hypotheses:

- H1: As previous studies suggest that techniques that present explicitly the attributes of the vector field perform better that techniques than don't, the first hypothesis is that OLIC and STATIC as they present both the direction and orientation in the graphic representation will be more accurate than the other dynamic techniques for orientation comparison. As IBFV and DT require participants to see the direction of the animation, they should be particularly inefficient for smaller sizes when comparing orientations.
- H2: Increasing distance and decreasing sizes seem to make distinguishing colors harder(Brychtová and Çöltekin, 2017). As the colored area of IBFV and DT is bigger than the colored area with the other techniques, our second hypothesis is that these two techniques will be more effective to compare colors, but that the difference will decrease for smaller sizes.

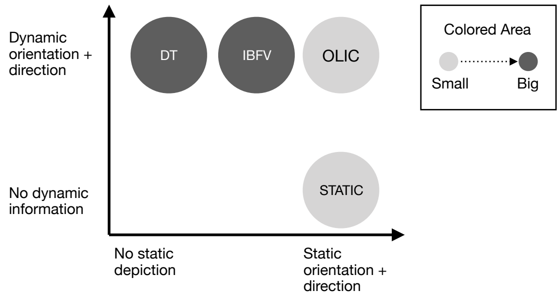


Figure 6: Classification of the techniques according to the information encoded dynamically and statically, and the colored area.

4.2 Participants and Apparatus

Sixteen unpaid volunteers (2 females), daily computer users, aged 22 to 56-year-old (average 37.3, median 42) participated in the experiment. All had normal or corrected-to-normal vision and did not suffer from color blindness. The experiment was implemented using WebGL in Javascript, and ran on a Laptop Dell 15" Retina (1600x900, 122 dpi) running Windows 10, equipped with a 2.30 GHz Intel Core CPU, 16 GB RAM and an NVIDIA GeForce GT 750M graphics. Participants were asked to seat at approximately 60 cm from the screen. Each participant completed 288 trials and the study lasted about 20 minutes per participant.

4.3 Procedure

We followed a $4x3x3$ within-subject design with 3 factors: TECHNIQUE, SIZE and ANGLE SPAN. TECHNIQUE corresponds to one of the four techniques described earlier. To choose the SIZE values, we took as reference the size of an icon (16 pixels), and we multiplied it by 2 and 4. The ANGLE SPAN value corresponds to the span between the lower and upper value of the two comparison values, as mentioned before.

The experiment was organized in technique blocks, the order of the techniques was counterbalanced across participants using a latin square. For the other factors, we generated a random order for each participant. For each technique, participants did 36 trials where they compared colors and 36 trials comparing orientations. For each technique, we had 3 ANGLE SPAN and 3 SIZE. Each SIZE x ANGLE SPAN combination was used in four trials, where we varied if the upper or the lower value was the closest angle or color. For example, for the ANGLE SPAN 30 and a reference angle of a, if the closest value is the lower

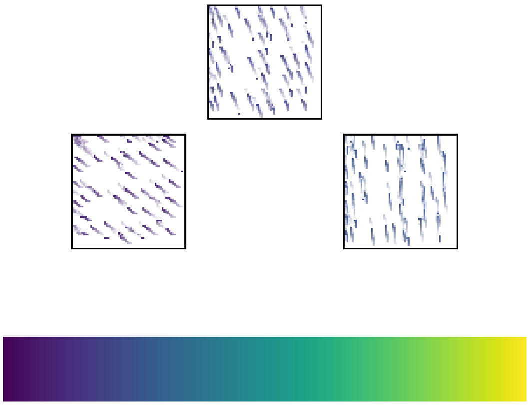


Figure 7: Example of a COLOR trial for OLIC technique. The participant is asked to chose the closest color to the reference value (on the top). The *Viridis* (bottom) color scale is only visible for these trials.

one, we would display the orientations a-10 and a+20. This results in 75 trials per block. We generated a random order of all the combinations of reference angles and colors, and then used the same order for each participant, as all the other conditions are randomized between participants.

Participants started each technique block with a training trial, that used both a color span and an ANGLE SPAN that was not used in the experiment. For each trial, participants first read a set of instructions explaining the study. They then were asked to select the closest color or angle. Figure 7 depicts a trial of color comparison and 8 depicts a trial of orientation comparison. The trials were grouped by comparison target, and participants either always started by comparing colors or orientations in each technique block. If comparing colors, the trial was complemented by a depiction of the *Viridis* color scale.

4.4 Results

4.4.1 Orientations

We used the Aligned Rank Transform (Wobbrock et al., 2011) procedure for non-parametric data to analyze the ERROR RATE. As Figure 9-(a) illustrates, TECHNIQUE has a significant effect on ERROR RATE ($F_{3,525} = 16.17$, $p < 0.0001$). A pairwise post hoc comparison revealed a difference between DT and all other techniques , but no difference between the other three techniques. ANGLE SPAN has also a significant effect on ERROR RATE($F_{2,525} = 35$, $p < 0.0001$), trials where the angle span was 15 presented a higher error rate than trials where the angle span was 30 that presented a higher ERROR RATE than trials where the angle span was 45 (Cohen's d between 30 and 45: 0.5,

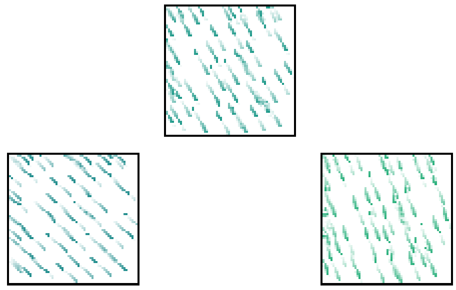


Figure 8: Example of a ORIENTATION trial for OLIC technique. The participant is asked to chose the closest orientation to the reference orientation (on the top).

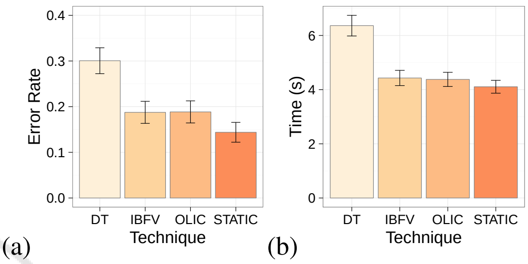


Figure 9: (a)Average ERROR RATE per TECHNIQUE for ORIENTATION. (b)Average TIME per TECHNIQUE for ORIENTATION. Error bars represent the 95% confidence intervals.

between 15 and 45: 0.85). Finally, SIZE does also have an effect on the error rate $F_{2,525} = 4.8$, $p < 0.0001$. Both smaller sizes present significantly a bigger error rate than the SIZE = 64. There are no effects due to the interaction between the factors (TECHNIQUE x SIZE: $F_{6,525} = 0.56$, $p = 0.5$, TECHNIQUE x ANGLE SPAN: $F_{6,525} = 1.86$, $p = 0.08$, SIZE x ANGLE SPAN: $F_{4,525} = 0.92$, $p = 0.45$, TECHNIQUE xSIZE x ANGLE SPAN: $F_{12,525} = 0.88$, $p = 0.56$).

TECHNIQUE has also a significant effect on TIME ($F_{3,45} = 6.95$, $p < 0.0001$, $\eta^2_G = 0.14$) as depicted in Figure 9-(b). DT is significantly slower than all the other techniques, that present no significant difference in between them. The SIZE also has an effect on TIME ($F_{2,30} = 5.62$, $p < 0.0001$, $\eta^2_G = 0.02$). SIZE=16

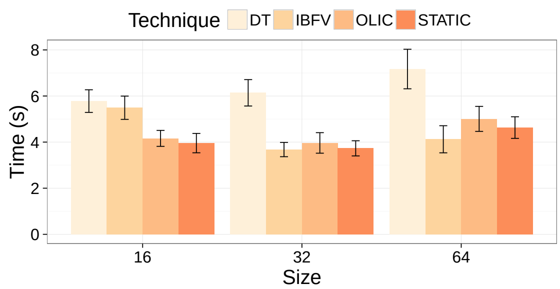
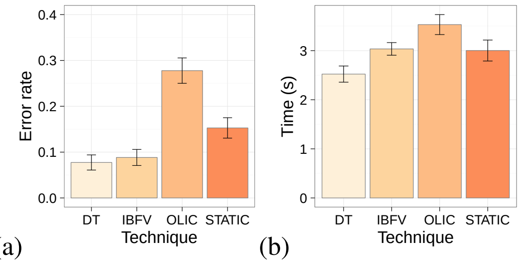


Figure 10: Average TIME per SIZE and TECHNIQUE for ORIENTATION. Error bars represent the 95% confidence intervals.



(a) (b)

Figure 11: (a) Average ERROR RATE per TECHNIQUE for COLOR. (b) Average TIME per TECHNIQUE for COLOR. Error bars represent the 95% confidence intervals.

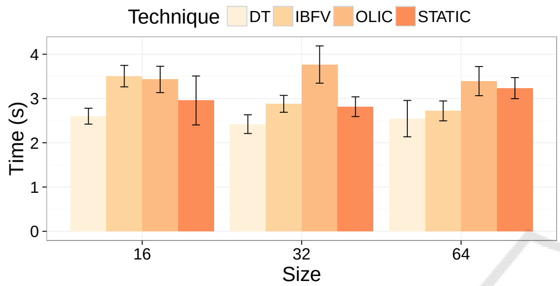


Figure 12: Average TIME per SIZE per TECHNIQUE for COLOR. Error bars represent the 95% confidence intervals.

takes longer than SIZE = 32, and SIZE = 64 takes longer than SIZE = 32. The ANOVA reveals a significant TECHNIQUE x SIZE interaction effect ($F_{6,90} = 3.9$, $p < 0.0001$, $\eta^2_G = 0.02$) on TIME, ad depicted in Figure 10. For the SIZE = 16, IBFV and DT are significantly slower than OLIC and STATIC, but for SIZE = 32 and SIZE = 64, there is no significant difference for IBFV, OLIC and STATIC, and all of them are faster than DT.

4.4.2 Colors

As for ORIENTATION we used the Aligned Rank Transform procedure for non-parametric data to analyze the ERROR RATE. TECHNIQUE also has a significant effect here on ERROR RATE ($F_{3,525} = 46.7$, $p < 0.0001$), as depicted in Figure 11-(a). A pairwise post hoc comparison reveals that OLIC is the more error-prone technique, followed by STATIC. DT and IBFV present the lowest error rates and present no significant difference between them. The ANOVA also reveals an effect of SIZE($F_{2,525} = 11.6$, $p < 0.0001$). The condition were SIZE = 64 was less error-prone, than SIZE = 16 and SIZE = 32. There is also an effect of the interaction SIZExTECHNIQUE($F_{6,525} = 2.9$, $p < 0.0001$), as depicted in Figure 13. When SIZE = 16, there is only a significant difference between OLIC and IBFV. But when SIZE = 32 and SIZE = 64, DT and IBFV are no different but are different from OLIC and STATIC, the last one being significantly less error-prone than OLIC. The ANOVA also reveals an effect of ANGLE SPAN on ERROR RATE($F_{2,525} = 4.58$, $p = 0.01$). The results suggest that the ANGLE SPAN = 15 is less error-prone than the other two conditions. There is also an effect of the interactions ANGLE SPANxTECHNIQUE($F_{6,525} = 2.89$, $p < 0.0001$), SIZE x ANGLE SPAN($F_{6,525} = 2.89$, $p = 0.02$), and TECHNIQUE x SIZE x ANGLE SPAN($F_{12,525} = 2.56$, $p < 0.0001$). Looking at each TECHNIQUE and SIZE individually, we found no effect for the different values of ANGLE SPAN. Looking at each SIZE per TECHNIQUE, we only find an effect for OLIC for the SIZE = 16, where the ANGLE SPAN = 15 presents less errors than the ANGLE SPAN=30.

TECHNIQUE ($F_{3,45} = 5.39$, $p < 0.0001$, $\eta^2_G = 0.067$) and TECHNIQUE x SIZE ($F_{6,90} = 2.68$, $p = 0.02$, $\eta^2_G = 0.044$) also have an effect on TIME for COLOR trials as depicted in Figure 11-(a). DT and STATIC are significantly faster than IBFV that is faster than OLIC. As depicted in Figure 12, for all SIZE values, DT is the fastest technique. It is significantly faster than IBFV and OLIC for SIZE = 16, but not from STATIC. For SIZE = 32, DT is significantly faster than all the other three, IBFV and STATIC are significantly faster than OLIC. For SIZE = 64, DT is only different from OLIC, that is the slowest no matter the size.

5 DISCUSSION

The graphic depiction of both direction and orientation does not seem to offer an advantage for OLIC in comparison to IBFV and STATIC overall for ORIENTATION comparisons, H1 is rejected. Also, contrary to what we expected, the SIZE does not seem to have an effect on the ORIENTATION perception accuracy. However, it does impact the time measure. For the smaller SIZE, OLIC and STATIC are faster. This could mean that the depiction of both orientation and direction that these techniques present is especially useful in smaller sizes, when is more difficult to see the direction and orientation of the animation. However, the dynamic aspect of OLIC does not seem to be useful enough to make it faster than STATIC.

IBFV and DT are the most accurate technique for COLOR comparison, and thus H2 is supported; having a more dense representation of the color seems to make a difference for an accurate color comparison. In fact, the results achieved with these techniques are similar to the ones presented in the recent study of Liu et al. (2018). OLIC is the worst technique for comparing colors. This difference depends also on the size; for the smallest size, STATIC is no differ-

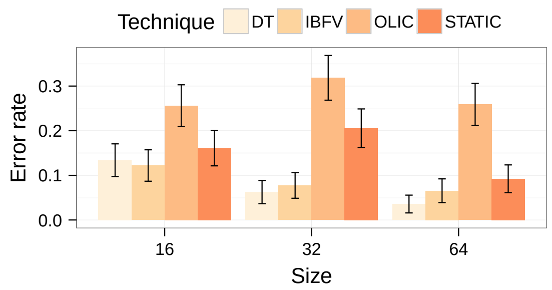


Figure 13: Average ERROR RATE per TECHNIQUE for COLOR. Error bars represent the 95% confidence intervals.

ent from IBFV and DT. As the size decreases, the difference of sizes between the techniques decreases as well, and thus the results agree with the relationship between size and color comparison (Brychtová and Çöltekin, 2017). We can hypothesize that OLIC does not perform well for the smallest size because contrary to STATIC it distorts the color by varying its luminosity across the particle. Regarding time, DT is the fastest technique. As DT uses a translating texture, it does not transform the color in any way, contrary to IBFV that blends the color with the noise texture at each iteration. This could explain why the color comparison with DT is fastest.

Surprisingly, we found an effect of ANGLE SPAN in the accuracy of COLOR trials, that suggest that when the animations present a smaller ANGLE SPAN, participants are more accurate comparing colors. The difference is significant when ANGLE SPAN=15, where the animations' orientations are at a distance of 5 and 10 degrees of the reference animation. We could hypothesize that the orientation difference might affect the color comparison, making easier to compare color when the angles are closer. However, further studies are needed to test this hypothesis.

6 SUMMARY AND FUTURE WORK

The results of our study suggest that the dynamic component of IBFV enables users to compare ORIENTATION as accurately as a static technique and COLOR as accurately as presenting the color without distortion. We recommend thus the usage of this technique when depicting those two visual variables together. However, the results might depend on the size of the depicted area. If the area to display is too little, perceiving the orientation with IBFV becomes difficult, and an alternative technique might be better, such as STATIC.

Our study presents multiple limitations. First, we tunned the different techniques in a way we thought they better depicted both the color and the orientation. But this design choices might have hampered some techniques. For example, we chose to apply the color to OLIC particles, instead of applying it to the background. Several examples on the web instead use white semi-transparent particles on top of a colored background. We chose this design to avoid introducing a third color to the technique, and to keep the particles visible. However, to keep the OLIC particles distinguishable, they cannot be very dense, making the color comparison more difficult than with the other techniques.

Second, to keep the design space manageable, we did not control for the specific angles or color values. Some participants mentioned that comparing orientations with light colors such as yellow was more difficult than with darker colors, especially for the IBFV technique. Also, some angles or quadrant comparisons might be easier than others. Further studies could be designed in order to test these hypotheses. Furthermore, we could reproduce the study using an iso-luminant color scale (Gregory, 1977), to avoid the effects of lightness variations.

Dynamic techniques also offer the possibility of mapping data dimensions to the parameters of the animation. In this study, we focused on ORIENTATION and COLOR because they present a higher granularity. However, some animation variables such as frequency and speed have already been used successfully in the case of animated textures in graph edges (Romat et al., 2018), and using them in animated textures is an interesting line of future work.

ACKNOWLEDGEMENTS

This research was partly supported by SESAR H2020 project ENVISION grant agreement No 783270.

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