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Andrew W. Kruse, Andrey S. Alenin, Israel J. Vaughn, J. Scott Tyo, "Overview of visualization strategies for polarimetric imaging data," Proc. SPIE 10655, Polarization: Measurement, Analysis, and Remote Sensing XIII, 106550S (16 May 2018); doi: 10.1117/12.2304678

Event: SPIE Commercial + Scientific Sensing and Imaging, 2018, Orlando, FL, United States

Overview of visualization strategies for polarimetric imaging data

Andrew W. Kruse[*], Andrey S. Alenin, Israel J. Vaughn, and J. Scott Tyo

University of New South Wales Canberra, Northcott Drive, Campbell ACT 2612, Australia;

ABSTRACT

Visualizing polarimetric imaging data is a difficult task due to its multidimensional nature, and there have been many different approaches to develop techniques for displaying this information. Currently, there is no method for producing effective visualizations, or evaluating their performance in accomplishing their intended goals. A task-based design process can be used to make sure that the unavoidable biases that occur in these visual representations match the biases required for effectively interpreting the information, relationships, and features within the data. As the field of polarimetric imaging grows and extends into other fields, some standardization of effective visualization techniques may be beneficial in communication and continued growth.

Keywords: Polarization, data visualization, visualization design, polarimetric imaging, visualization tasks, data analysis

1. INTRODUCTION

The fundamental difficulty in displaying the unique information that polarization imaging measures arises from the fact that humans are polarization-blind. Consequently, in order to be visually represented, this data must go through other channels in the human visual system (HVS). Most notably, mapping into color vision is often used because of its structural similarities to polarization imaging data.[1] However, other techniques for utilizing other visual cues such as motion, texture, and flickering have been proposed.[2] With few exceptions, the design of visualizations used in polarization imaging are not analyzed for effectively achieving a particular goals. In addition, the goals of the visualization often do not factor into design choices, even though the tools to do so are available in the vast amount of literature on visualization design. Without concern for design, the visualizations in polarimetric imaging may be ineffective, ill-suited for the intended task, or lead to biased or misleading depictions of data.

The primary goal of this paper is to initiate discussion on the effective, task-oriented use of visualizations for the varying types of data in polarimetric imaging. As polarimetric imaging is often a tool used by many fields to study different phenomenon, specific techniques that are popular within disciplines are often unknown to those in other disciplines, even though the types of data may be similar. To illustrate this, consider the method of superimposing the polarization ellipse as proposed by Gagnon and Marshall.[3] Although this method was novel for the purpose of imaging polarimetric properties of biological specimens, the general method has been used in astronomy for decades.[4] We believe that the knowledge of effective visualization strategies should be as accessible as possible to anyone using polarimetric imaging.

Often times, the purpose of a visualization is to explore the data and look for features or relationships. Visualizations used for analysis are not necessarily good for communicating to an audience. An experienced researcher can navigate a complicated visualization technique to explore their data, but this does not mean this technique will be the most effective method of communicating ideas to an untrained audience. A good rule of thumb is to make certain that the first impression one would have upon viewing the visualization should match what the communicator is trying to express. Explanation on how to understand the visualization (eg colormaps) should enhance the initial impression instead of causing reinterpretation.

It is well accepted that good techniques for writing are necessary for authors to communicate ideas. Similarly, good techniques for creating visualizations can express things that words alone cannot. However, proficiency

[*]a.kruse@student.adfa.edu.au

Polarization: Measurement, Analysis, and Remote Sensing XIII, edited by David B. Chenault, Dennis H. Goldstein, Proc. of SPIE Vol. 10655, 106550S · © 2018 SPIE · CCC code: 0277-786X/18/$18 · doi: 10.1117/12.2304678

in communicating through visualizations is undervalued compared to writing.[5] Scientific authors may spend countless hours editing, rewriting, and scrutinizing every sentence of a piece of work and yet not put a similar amount of effort in constructing effective visualization strategies.

2. TASK-BASED DESIGN

A good starting point for effective design is to define the purpose of the visualizations in terms of tasks. Just as different types of imaging are more useful to study a certain phenomenon, different types of visualizations and their variations are more applicable to assisting tasks. In visualization literature, there is no consensus on either the exact definition of a "task" or the proper way to categorize a task. Instead of choosing one of dozens of hierarchies to define any given task, it would be easier and more productive for the visualization designer to ask questions about the intended outcomes of the representation. These questions can range from broad "Who is the intended audience?" or "Is this exploratory analysis or am I looking for specific relationships?" to specific "Does this contain high frequency spatial information?" While there are some tasks that have accepted definitions, the questions the designers ask do not need to conform to those describe in visualization literature. However, it may be useful to list some of the well-defined tasks[6] here for a starting point.

Identification or Lookup : this task involves extracting data values. In this task, the goal is not to directly express relationships between values but instead to maximize the ability to identify the value of a data point or object. Equal visual importance as well as maximizing the number of colors is important for this task. This task does not necessitate a perceptual ordering. Setting AoP to a hue map is accomplishing the identification task.

Comparison: this task is for expressing quantitative differences between data points. Comparison requires perceptual ordering. In this sense, users should be able to tell the relations between points without relying on a key. Examples of perceptually ordered cues are lightness, colorfulness, length, and opacity. Visualizations that primarily support comparison task should not be used when the data does not fall into an order, since that would impose an inaccurate structural appearance upon the data.

Localization: this task is meant to highlight regions of interest and suppress everything else. This is very useful to immediately differentiate an area that has a specific polarization signature that is of interest.

Additionally, the types of data are important for matching with the available types of visual channels.

Monotonic: data is in a range of low to high. DoP often appears as monotonic. Visual channels such as colorfulness, lightness, length, and opacity are monotonic.

Diverging: data falls on either end of some critical value. This critical value could be the point between negative to positive, left or right, up or down, or could have theoretical connotations. DoCP is often diverging due to values being right-handed or left-handed. Opponent color channels are a diverging visual channel.

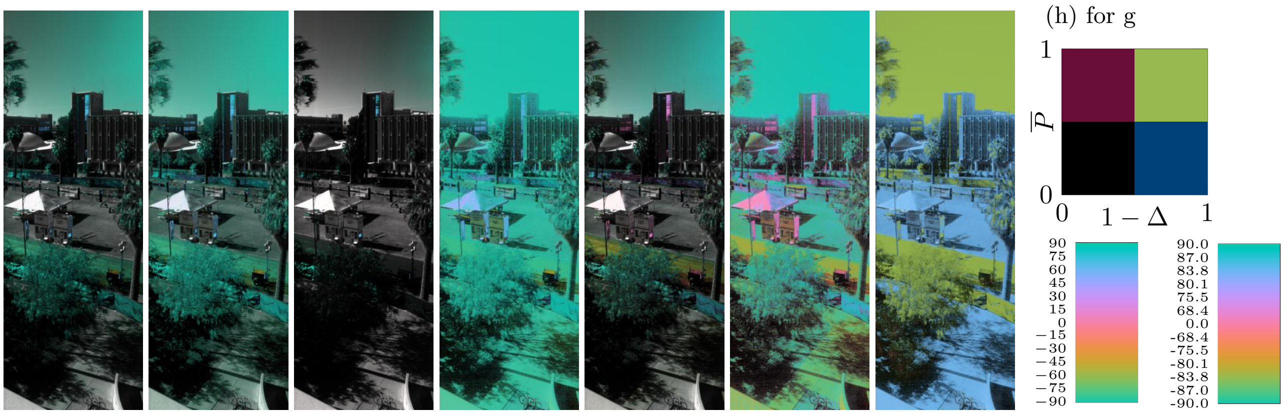
Periodic: data that is cyclical, where there are no ends. AoP is often periodic, especially when the coordinates are set arbitrarily. Hue and geometric angle are periodic visual channels.

Categorical: Data does not have any order, but is put into some group. Sufficiently separate hues or shapes can be used to represent categorical data.

Continuous: Data does not fall into discrete steps or categories and requires visual channels that are also continuous.

Discrete: Data can only have certain values. Continuous data can become discrete when binned.

Typically, the design for polarization visualization has been done prior to assigning tasks. That is, the visualization is created without the input from the functions the user will be performing. Instead, it was assumed that the visualization would be able to support all of the various tasks the user may decide to perform. This is abundantly clear looking at the history behind the commonly used color fusion method for linear polarimetric imaging. This method was designed by matching the similar dimensions of color and linear polarization. However, there was no description of the tasks this mapping was meant to support or any supportive reasoning for its effectiveness. Although more generally introduced earlier,[1,7] the method was formalized in 1992[8] using the HSV color space. Only recently was this method updated so that dark regions with high polarization were visible. Before this update, obtaining polarimetric information from these regions was not possible with this visualization.



(a) (b) (c) (d) (e) (f) (g) (i) for a-d (j) for e-f

Figure 1: Series of visualizations resulting from implementing different sets of tasks outlined in Table 1. Ground MSPI data,[9] $\lambda = 660$ nm.

Label	Featured Tasks	Design Implementation	Figure
T1	P1, A1, A2, S1, L1, L2	as defined in[10]	1a
T2	P2, P1, A1, A2, S1, L1, L2	$\overline{P} = P^x, x < 1$	1b
T3	P3, P1, A1, A2, S1, L1, L2	$\overline{P} = P^x, x > 1$	1c
T4	D1, A1, A2, S1, L1, L2	$\overline{P} = \Delta'$	1d
T5	P1, A3, S1, L1, L2	$\overline{\psi} = erfc(\psi)$	1e
T6	D1, A3, S1, L1, L2	combination of T4, T5	1f
T7	D3, S1, L1, L2	$\overline{P} = max(\Delta, P)$ $\overline{\psi} = 4/3\ round(tan^{-1}(\Delta/P))$	1g

Table 1: Design implementation resulting from task sets and their corresponding figure.

Thus this method was not supporting one of the most ubiquitous tasks: comparison of degree of polarization. Because this task was not implemented into the design, there was nothing to ensure that this task would be supported. Thus for future visualization methods, similar sources of ineffectiveness can be avoided by beginning with a set of required tasks as the basis for choosing visual channels for encoding information.

The task-based design structure is already well-established in visualization literature, and has been implemented for many applications. However, it has not been generally implemented for the application of polarimetric imaging. With the task-based design structure, the majority of the decisions are made at the task level before the visual channels are chosen. With an understanding of the visual channels available, the visualization can be generated strictly from the set of tasks. This contrasts the majority of previous strategies where the visualization designs were created before assigning tasks. The example later in this paper shows in detail the methodological construction of a visualization based on selecting and balancing specific tasks. Additionally, meaningful variations can be derived by replacing some of those tasks. While there are a great number of possible tasks that could apply to polarimetric imaging, the following list is a collection of useful tasks appropriate for describing a large number of scenarios as well as a few specific applications. In some cases, two tasks may coexist in a visualization without issue. In other cases, two tasks may be incompatible or outright contradictory. And lastly, tasks may coexist in some diminished form in a similar way to a function that is optimized over a weighted combination of variables.

P1: Comparison of degree of linear polarization (DoLP). The user is able to perceptually order the amount of DoLP within the scene, and make judgments on the relative distances between values that correspond to perceptual distances. In this, users would be able to look at two regions of interest and quickly determine which has a stronger amount of polarization without consulting a reference guide. This may contrast with other **P** tasks since DoLP would have to be represented by a linear perceptual channel. This does not require the user to be able to extract the exact values.

P2: Localizing polarized areas from unpolarized. The user is able to quickly determine which areas have an appreciable amount of polarization. This may contrast with other **P** tasks since low but significant polarization signals may be amplified to differentiate them from the unpolarized background.

P3: Localizing areas with high polarization from areas with middle to no polarization. In this, the user would be able to differentiate the strongest polarization signals. This may contrast with other **P** tasks since differentiation may cause suppression of middle and lower polarization signals.

L1 Determine physical attributes of the objects in the scene. This includes being able to determine location, shape, size, and surrounding context of everything within the scene in a recognizable fashion. Additionally, each polarimetric channel is located at the same physical location and not separated in space. Visualizations incorporating this task would appear more image-like than it would without it.

L2 Comparison of intensity. Similarly to **P1**, users are able to perceptually order and compare relative intensities.

S1: Assess polarimetric channels independently. This task involves the user being able to perform tasks on each individual polarimetric channel without hindrance by or confusion with the other channels. Without this task, perceptual channels represent a mixture of polarimetric channels.[10]

A1: Identification of full range of angle of polarization (AoP). The user is able to extract the value of any angle with maximized accuracy.

A2: Comparison of magnitude difference in AoP. Since AoP is periodic, the direction of change does not need to conform to a perceived ordering. However, the magnitude difference can be determined by the ordering of the magnitude of perceived difference. Combined with **A1**, the user would be able to perceive gradients or dissimilarity between angles smaller than the margin of error of the **A1**. While the user may not be able to quantify the difference using **A1**, they would still be able to compare the magnitude of change or difference.

A3: Identification of AoP within the neighborhood of a reference angle. This can be seen as an extension of **A1** in which there is a greater range of perceivable difference between angles when they are close to some reference angle. This task may be important when there are small but appreciable differences between angles that correspond to distinct regions. For example, in a scene that is dominated by reflection of a linearly polarized source, the resulting polarization signals will often be similar but distinctly different to the source. However, the small differences may only be discernible when there are large corresponding perceptual differences. Generally, this will contrast with the ability to identify angles that are not close to the reference angle due to the limited number of identifiable characteristics in any perceptual channel.

D1: Comparison of AoP confidence. Using the variability metric Δ from our earlier work,[11] tasks can be performed on the corresponding confidence metric $\Delta' = 1 - \Delta$ directly. This would work exactly like **P1** task, although the two may be in contrast when there are not enough linear perceptual channels available.

D2: Identification of DoLP vs Δ'. As our previous work depicted, the confidence in the AoP does not necessarily correspond to a significant amount of DoLP in some regions. Therefore, polarization signals could be labeled exclusively to one of the following: no polarization, high confidence but low DoLP, high confidence and high DoLP, and low confidence and high DoLP (false polarization). This function of this task is to identify the category of each polarization signal.

One set of these tasks **T1** defines the basic structure of the visualization mapping strategy formulated by our upcoming publication.[10] One solution that incorporates these tasks utilizes the color channels within the perceptually uniform channels within the color model CAM02-UCS.[12] This color space is defined by the cylindrical channels of lightness J', colorfulness M', and hue h corresponding to axial position, radius, and polar angle. A similar solution space was argued for by Solomon.[13] However, the model he proposed cannot fully support the tasks **T1**. Instead, because the human visual system's perception of color does not match a nice cylindrical shape, there are conflicts between tasks. To resolve this, the tasks were weighted in such a way that **S1** was limited to only having DoLP and AoP to be represented by completely independent perceptual channels, and the intensity range, represented by the lightness channel, was dependent on DoLP. While it is possible to fully support **S1** by creating a cylindrical subset of the entire color space, the limitations this would place on the colorfulness and lightness would significantly hinder **P1**, **L1**, and **L2**. order to support **P1**, the tasks **S1**, **L1**, and **L2** had to assume less support. The resulting mapping strategies are

$$\begin{aligned} g_h(\overline{\psi}) &= 2 \cdot \overline{\psi} \\ g_{M'}(\overline{P}) &= max(c) \cdot \overline{P} \\ g_{J'}(\overline{I}, \overline{P}) &= \overline{I} \cdot (J'_1 - J'_0) + J'_0 \\ J'_0, J'_1 &= \{J' : c(J') = g_{M'}(\overline{P})\} \end{aligned} \tag{1}$$

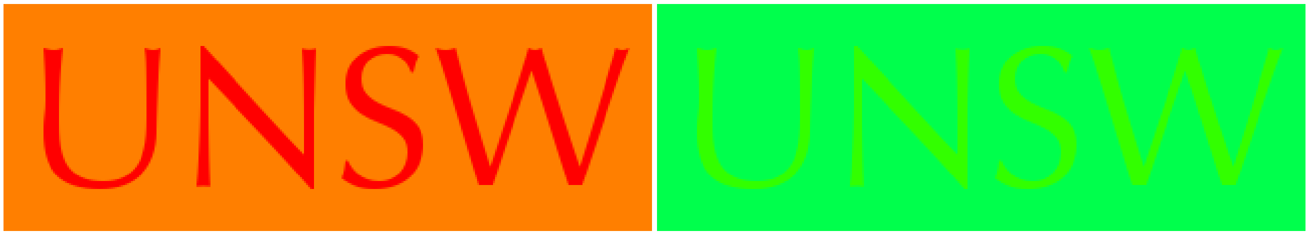
where g_x is the mapping function of perceptual channel x, P is DoLP, I is intensity, ψ is AoP, c is a curve representing the edge of the rotationally symmetric subset of the UCS color space, and the bar above the channels represent any and all preparations of the channel including normalization, nonlinear stretching, binning, etc. It is in this preparation step where different tasks can be implemented easily into this structure. Here we will discuss 6 different task variations within this structure.

Task set **T2** implements the task **P2** at the detriment to **P1**. In this case, the colorfulness channel is amplified by a for regions with low and moderate polarization in order to differentiate them from the unpolarized areas. While the polarization differences no longer linearly correspond to perceptual differences, the ordering aspect of **P1** is still apparent. Looking at Fig. 1b, it is easier to differentiate polarized areas in comparison with Fig. 1a. In contrast, task set **T3** does the opposite, where only the regions with the highest polarization are differentiable. This makes it extraordinarily easy for the user to immediately know the location the most significant polarization signals. Task set **T4** allows the user to compare the confidence in the AoP, but consequently removes the ability to compare the DoLP. It can be seen in this variation how the majority of the scene displays a confident AoP that is similar to the scattering angle. While Fig. 1a displays similarity between the AoP within the scene, implementing a task set **T5** that allows for more identifiable colors within the range close the scattering angle displays the significant differences between areas with seemingly similar polarization signatures. This can additionally be combined with **A3** to display the differences between similar signals not shown in Fig. 1d. To emphasize the fact that areas with high AoP confidence do not necessarily have a high polarization, the task set **T7** would support this identification. In this, a polarization signal falls into one of the four categories discussed earlier. This would also help identify sources of false polarization.

3. BIASES

Not only does beginning with a task-oriented basis establishes the ability to perform the tasks required for user interpretation, but it prevents unintentional tasks from being imposed that would introduce unwanted biases. This is due to the inseparable connection of tasks to biases. The set of supported tasks creates the biased lens through which the user must visually interpret the information. The notion that a visualization could ever be unbiased is a misconception, since the processing channels in the HVS are themselves biased. The job of the visualization designer is therefore to make sure that the unavoidable biases in the visualization match the biases needed for interpretation. The chosen sets of tasks can be considered a set of biases that are desirable for interpretation, and the sets of tasks that are not supported are the biases that are not desirable in that particular instance.

To help explain how unintentional biases can creep into visualizations, consider these three design criteria outlined by Kindlmann and Scheidegger: Representation Invariance (RI), Unambiguous Data Depiction (UDD), and Visual-Data Correspondence (VDC).[14] RI states that arbitrary changes to the system should not affect the ability to perform tasks in the visualization. Failing to satisfy RI allows different biases to be introduced that correspond to data that is meant to be equally biased. This is of particular concern for polarimetric imaging, where the choice of coordinates for the AoP are arbitrarily set for the system or image. This can be interpreted in this sense as "Rotational Invariance". If choosing new axes results in the impression of the visualization to change, this violates RI. Considering a hue mapping for AoP, the arbitrary decision of whether the horizontal angle is represented as red, blue, or green, should not have any meaningful affect on the interpretation. Secondly, UDD states significant changes in the data must be accompanied by significant changes in the visualization. Failing to do so would mean that the user misses key information. Thus, this visualization would bias the user into perceiving that information as insignificant. Similarly, VDC states that changes that are not significant should



(a) (b)

Figure 2: Different representations of the same angular difference for AoP mapped to Hue in HSV

not be represented by large changes in the visualization. This would mean that the visualization would create biases such that the user would perceive insignificant information as significant. Fig. 2 shows two representations of the same angular difference in polarization when the coordinates are rotated. In this example, the common periodic colormap created by cycling through hues at maximum saturation and value in HSV. The fact that the two representations express drastically different color differences means that this visualization system violates RI. Moreover, Fig. 2b also violates VDC, since a significant change in AoP is not expressed as a significant change in perceived hue.

It may be helpful to approach biases in a quantifiable form. Our attention is not drawn equally for the various representative variables used for visualizing. Bernard et al define several metrics for colormap attributes that are important for the application of tasks.[15] We can look at their metric for attention steering. Attention is steered toward bright and colorful features, which makes those features appear as more important or prominent than other features. They used this concept to define a color's "attention" as the hypotenuse of lightness and chroma in CIELAB. For the given set of colors in a colormap, the standard deviation is a measure of how unequally the attention is distributed for the various colors. This metric could be applied generally for any representative variable, provided there is some measure of attention. Low values are desirable when data values are meant to be displayed with equal importance, while higher values are desired when trying to highlight data values. For AoP, unless there is a specific angle or set of angles that are of more importance, it generally is desirable to show equal importance across the entire range. In contrast, higher values for degree of polarization (DoP) are usually of more importance than smaller values. In this case, the viewer's attention should be steered toward areas with high polarization. A desirable metric in this case would describe how the attention increases, or the velocity of attention. More abstractly, it is desirable that the visualization steers attention toward values that faithfully correspond to intended biases of the importance of values.

When looking at combinations of tasks, a solution that supports all of the tasks could be achieved by optimizing their associated metrics. Perceptual linearity relates to how perceptual differences correspond to data value differences. This can be applied globally, where the ratio between perceptual difference and value difference is always equal. For a globally linear system, doubling the value difference should double the perceptual difference. Linearity can be applied locally, where each discrete step in the perceptual representation represents the same amount of value difference. Color exploitation is a measure of the number of colors that are just noticeable different, which also represents how much of the color space is being used. If we look at a simple case involving the comparison and identification tasks on a single variable, the colormap that supports both of these tasks is the solution of an optimization of a weighted cost function involving metrics of local and global linearity and color exploitation. Identification requires many discernible features, while comparison requires the features to be in a linear perceptual order. This solution takes the form of "spiral" colormaps, that gets its name from the colormap spiraling from dark to light in 3D color space.[16] These maps sacrifice some global linearity which allows a greater number of colors, and it sacrifices the range of colors to preserve some global linearity. These types of colormaps are usually set as the default for most applications. Examples include matplotlib's viridis[17] and MATLAB's parula.[18] While there is no evidence that the design of these colormaps employed a literal optimization process, it is nonetheless helpful to view their solution as figuratively functioning as a mathematical solution. Such optimization solutions have been proposed,[19] yet have not been fully explored.

4. CONCLUSION

The visualization of polarimetric imaging data is inherently difficult due to the multidimensional nature of the measured parameters. Because any visual representation must contain some biases, a task-oriented design method is useful in maintaining that those biases represent how the user is meant to interpret the information. The design of a visualization will naturally follow once the tasks are carefully chosen, as demonstrated in Table 1. Simple changes to the supported tasks can produce significantly different visualizations that lead to distinct conclusions, as indicated by Fig. 1. If the tasks are not chosen carefully, or in the case of much of the current polarization visualization, not consciously chosen, these conclusions may not represent what is intended or backed by evidence. Hopefully this task-based method will be a starting point for more effective visualization design that can be used by anyone using polarimetric imaging.

Funding. Asian Office of Aerospace Research and Development (FA2386-15-1-4098).

Acknowledgements. Ground MSPI data provided by C. L. Bradley and R. A. Chipman from University of Arizona.

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