A Scientific Visualization Schema Incorporating Perceptual Concepts

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Abstract

Scientific Visualization is the process of transforming numeric scientific data into an image or images that, when presented to a human observer, convey insight or understanding of the data. The process is often described by means of a visualization pipeline *that involves the stages of transforming the data into an intermediate representation, mapping the results into graphical entities termed* visualization icons *and displaying them. In this paper we extend the traditional pipeline model to include two additional stages that take place within the observer:* visual perception *by the visual system and* cognition *by the human brain. We review the literature on the human visual system focusing on issues relevant to scientific visualization, such as* preattentive processing *and suggest a classification of visual attributes according to information accuracy, information dimension and spatial requirements. Using this schema we show how concepts from human visual perception and cognitive science are related to the visualization process and how this relationship can be utilized for creating more effective visualizations of scientific data sets.*

Keywords: Scientific visualization, Human visual perception, visual attributes, visualization icons

1. Introduction

A multidimensional data set L_m^n consists of m *independent variables* representing the data domain and n *dependent variables* defined over the domain. In many applications the independent variables define a two or three dimensional spatial domain and the data set is then referred to as 2D and 3D data, respectively. An additional independent variable can be introduced by considering time. Both dependent and independent variables can be either *discrete* or *continuous* and can have a *finite* or an *infinite* range of values. Common examples for dependent variables are scalar fields ($n = 1$) such as temperature, vector fields ($n = 3$) such as velocity, and symmetric tensor fields ($n = 6$) such as stress. Many scientific data sets consist of multiple fields defined over the same domain resulting in a high-order space of dependent variables. Scientific visualization is the process of representing multi-dimensional data by an image (the *visualization*) in order to improve its comprehensibility. The visualization process can be divided into three stages [7]: The *data transformation* stage converts raw data into a form more suitable for visualization. This can involve resampling, data type changes, subset creation, and the derivation of new quantities. The subsequent *visualization mapping* converts the raw data into a number of graphical entities (*visualization icons*) which represent one or more dependent variables over the whole or a subset of the domain. The final *rendering* stage displays the visualization either on a screen or by printing.

In order to increase the information content of a visualization it is important to understand how the rendered image is perceived and interpreted. We therefore denote the traditional visualization pipeline as a data encoding step and extend it by a data decoding step consisting of *visual perception* and *cognition*.

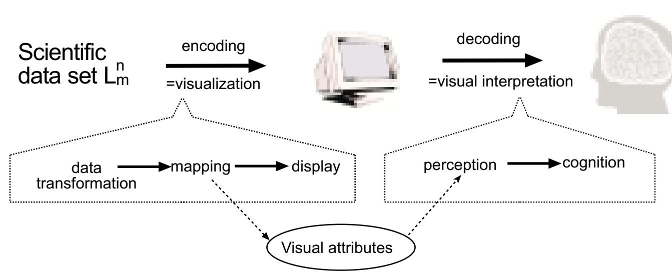

Figure 1. A visualization schema

The resulting visualization schema is shown in figure 1. The encoding and decoding step of our schema are connected via *visual attributes* such as geometry, position, and color, and *textual attributes* such as text and symbols which themselves are represented by simple visual attributes. A visualization is effective if the decoding can be performed efficiently and correctly. “Correctly” means that perceived data quantities and relationships between data reflect the actual data. “Efficiently” means that a maximum amount of information is perceived in a minimal time.

The biggest challenge in visualizing multidimensional data is that the visualization has to be displayed on a two-dimensional screen using colour as an additional output dimension. Animating a visualization introduces an additional output dimension which is frequently reserved for the independent time variable. Using the characteristics of human visual perception it is possible to simulate additional output dimensions. A third spatial dimension is obtained by using stereoscopic techniques or by using pictorial cues to simulate depth perception (see section 2). Several authors refer to texture as an independent output dimension which makes use of the brain ability to identify patterns. In addition the perceptual colour space is three-dimensional though limitations in human colour vision restrict its full usage and usually only two output dimensions, such as hue and lightness or hue and saturation, are employed.

We claim that an understanding of the human visual perception is important for the successful design and assembly of visualization icons to a scene. In the next sections we give an overview of human visual perception with particular emphasis on visual attributes and then explain how the results can be applied in order to create more effective visualizations.

2. Human Visual Perception

The human visual system consists of the eye which converts incoming light into nerve signals, the visual pathway, which transmits these signals and the visual cortex in the brain which interprets visual information. Visual information is processed by three types of nerve cells, which are sensitive to colour and contrast, edge detection, and orientation and direction of movement [5]. Higher order processing is responsible for the perception of stereoscopic depth and complex forms and concepts. The most basic integrated units of visual information are the visual attributes color, line orientation , and contrast which is fundamental for the perception of contours. Other basic perceptually significant attributes are transparency, position and size [16].

The perception of a scene is the result of two major processing stages. The initial *preattentive stage* allows perception of very simple features without conscious attention. An example is the instantaneous perception of a red dot in a cloud of blue ones. The underlying mechanism has been contributed to different sensory dimensions for basic visual attributes such that a unique feature in any dimension is immediately detected [3]. Preattentive vision seems to be dependent on primitive textural features such as length, width and orientation of simple elongated shape as well their end connections, angle orientations, and intersections [16]. Apart from these preattentive vision also exists for shape, curvature, closure, colour (hue), intensity and more complex visual attributes such as texture and depth [8]. Preattentive vision does not only apply to feature detection but also to region segregation and basic quantitative tasks such as estimating the percentage of red blobs in a cloud of red and blue dots [8]. Research indicates that preattentive features are ordered by importance with hue being the most important especially in dynamic environments [8].

The second principal visual processing step is the *focused attention stage* which involves conscious examination of a scene, rapid mental calculations and quantitative reasoning. This stage is responsible for identifying complex unitary objects and complex quantitative information.

2.1. Visual Attributes

The previous section introduced color, line orientation, contrast, transparency, position and size as basic visual attributes.

Using the concept of *trichromacy* a perceived colours can be represented as weighted sum of three *primary colours* red, green, and blue. A more intuitive representation of colour is given by the perceptual attributes *hue*, *brightness* and *saturation* which reflect the physical attributes *wavelength*, *intensity*, and *spectral purity*, respectively. The brain’s ability to locate a colours in this 3D space is limited and even colour experts have difficulties separating hue and lightness [3]. Furthermore coulour perception is influenced by the surrounding colours (colour illusions). For example, a colour patch is perceptually shifted by the colour of adjacent patches (*simultaneous contrast*). If colours of different intensities meet, non-existing intensity changes are perceived (*Mach bands*) [10]. Prolonged exposure to a colour can change perception of subsequent visual impressions since it produces an afterimage of the complementary colour [16]. In addition some black and white patterns can cause colour sensations (subjective colours) [16]

The brain utilizes low-level visual attributes for performing more complex visual tasks such as the perception of shape, Gestalt, and depth which together are referred to as *spatial vision* [5]. Other higher order tasks are figure-ground perception and texture perception. The involved visual attributes are called high-level visual attributes.

Texture is perceptually characterized by its spatial frequency, contrast and orientation [16]. Recognition of feature patterns is accomplished using the same texture primitives (textons) as for preattentive vision with line segment orientation being particularly important. Pattern detection is orientation dependent and is influenced by adaption (familiarity) [5].

Shape information is directly derived from luminance, motion, binocular disparity, colour, and texture, with luminance yielding shadow and subjective (illusory) contour information [3]. Shape perception is dominated by the curvature of the silhouette contour (figure-ground boundary) and 3D surface shading [9]. Current results indicate that diffuse shading is the most important shape cue whereas adding specularity does not improve perception of shape differences [15]. Shape perception is highly orientation dependent such that rotated versions of the same form can be perceived as different shapes. Perception can also be dependent on previous stimuli [16]. Familiar shapes and configurations can improve the recognition of a target if it is a part of them [16].

Depth perception is achieved using binocular vision and pictorial cues. Binocular vision includes disparity, convergence and motion parallax. The first expression refers to human beings having two eyes which are slightly displaced and therefore perceive different images of the same object. The displacement the retinal images of an object is converted by the brain to a depth information. Motion parallax is the effect that the relative distance an object moves determines the amount its image moves on the retina. Binocular vision can be achieved in visualization by using stereo goggles or VR Head Displays. Visual cues aiding depth perception are size, brightness, perspective, overlay (occlusion), texture gradient, and aerial perspective [9]. Aerial perspective stems from the observation that colours on the horizon usually appear bluish blurred. As a consequence the brain associates such colours with large distances.

The concept of *Gestalt* originates from the fine arts and expresses the notion that the "whole contains more information than the parts" [4]. Perception of Gestalt is influenced by proximity, similarity, continuation, closure, symmetry, and the *law of Prägnanz*, which states the the eyes tends to see the simplest and most stable figure [17, 16]. Context might also play a role in Gestalt perception [9].

Figure-ground perception describes the observation that an object can be instantly separated perceptually from its background [16]. This is due to physically different attributes of the figure and the background but is also influenced by size, angle, and association with meaningful shapes [16].

2.2. Classification of Visual Attributes

Not all visual attributes are equally well suited to display of quantitative information. For many attributes their perceived scale is a power of the actual scale (Steven's law) [1]. The power is close to one for the perception of length so that length variations can be estimated quite accurately. For area and volume changes the power is smaller than one so that small areas are usually perceived larger than they actually are and vice versa for large areas. In addition perception of visual attributes can be influenced by orientation, e.g., angles with a horizontal bisector are seen larger than angles with a vertical one [1]. Also it has been shown that slope changes influence the perception of vertical distances.

As a consequence the suitability of visual attributes for information encoding differs. We introduce the term *information accuracy* as a measure of how accurately a human can estimate a quantitative variable represented by that visual attribute. Cleveland shows that such a variable is most accurately represented by a position along a scale, and then in decreasing order of accuracy by interval length, slope angle, area, volume and colour as indicated below [1].

highest accuracy of representation ↑	position on scale
	interval length
	slope angle
	area
	volume
lowest accuracy of representation ↓	colour

More complex visual attributes are based on basic visual attributes. Depending which low level attributes dominate in the perception of a high level visual attribute the suitability for visualizing quantitative data can vary. For example, a spot noise texture consists of "smeared dots" having a length and direction [19]. The texture is therefore well suited for representing vector fields.

We suggest further differentiating visual attributes by their information dimension and spatial requirements. *Information dimension* refers to the number of dimensions inherent in the visual attribute. Length and slope represent only one dimension but colour can be used to represent at least two dimensions. Texture is usually composed of several basic visual attributes such as colour and the length and orientation of texture elements. The total information dimension is therefore the sum of the dimensions of the inherent basic attributes. An additional output dimensions can be represented by the spatial frequency of a texture. Similarly shape has been shown to represent multiple independent output dimensions.

We define the *spatial requirement* of a visual attribute as the smallest unit of space (ie. pixels on a screen) necessary to identify a piece of information. Whereas colour has a minimal spatial requirement only limited by the resolution of the human visual system a texture requires a much larger space of the output medium to enable the viewer to identify inherent information. For example, a pixel of a spot noise texture contains no information since neither direction nor length of the represented vector field are apparent.

The *information content* of a visual attribute can now be defined as the product of information accuracy and information dimension. The *information density* is given by dividing the information content of a visual attribute by its spatial requirement.

3. Creating an Effective Visualization

In order to create an efficient visualization scientific data must be mapped to visual attributes in a way that optimizes perception and understanding. The task is difficult since the perception, interpretation and comprehension of visual input is influenced by context, attentional focus, expectations, prior knowledge, past experiences and subjective biases [8]. The visualization task can be facilitated by using standardized visualization icons for scalar, vector and tensor fields. Often this requires an intermediate data transformation step such as a tensor decomposition, coordinate transformation or an interpolation. However considerable freedom remains when mapping data to visual attributes of an icon. Also when displaying multiple fields simultaneously perceptual interferences between visualization icons can occur. The next section summarizes issues concerning the application of visualization icons.

3.1. Mapping Data onto Perceptual Attributes by Using Visualization Icons

Visualization Icons are graphical objects which encode scientific data by visual attributes. In general the independent variables of scientific data are reflected in the spatial (and temporal) positions of the icons leaving colour, textures, shape and orientation to encode the dependent variables. The mapping between variables and attributes is usually determined by the intended function of the icon, which include display quantitative information, drawing attention, and showing correlation.

Quantitative information is best displayed by length and is therefore reflected in the shape of an icon. Example are vector arrows and height fields. Attention can be drawn to a target by using bright or highly saturated colours, movement or change, and sharp boundaries [13]. Target identification is also influenced by linear separation, colour category, and colour distance. If the complexity of the scene allows it, instant target identification can be achieved by using preattentive features. Finally it has been suggested that correlation between related data sets is perceived most easily when similar visualization icons are used [10].

Several other issues have to be considered when employing visual attributes:

Colour is a complex attribute due to non-linearity in human colour perception and psychological influences such as colour metaphors. If colour is used in the segmentation of a scene no more than five colours should be used [3]. Pastels should be used to show continuities (since they blend into each other) and clashing colours to discriminate areas [10]. Also colour should suggest meaning (metaphor) and related colours should be used for clusters of similar values or series of images [2]. Colour discrimination just by hue is difficult [6] so if features are emphasized different saturations should be employed. Gray scales minimize complexities due to psychological influences and are especially popular in medical imaging due to their greater range of contrast [10].

Continuous data can be represented by associating scalar values with a colour scale. A useful property of a scale is that the the order and distance between perceived colours is equivalent to that of the associated scalar values. The scale should additionally accentuate important features while minimizing less important or extraneous details. Artistic or aesthetic quality can also be important. Note that a colour scale can not be judged in isolation since colour illusions such as simultaneous contrast can reduce its effectiveness.

Various colour scales have been presented in the literature [14, 12]. A special case is the *linear gray scale* which varies linearly from black to white. Levkowitz and Herman report that this scale resulted in a better identification of simulated features in medical images than any of the tested colour scales [12]. Adding a constant hue to a gray scale creates a *univariate colour scale*. The main disadvantage of gray scales is their limited perceived dynamic range of only 60-90 noticeable value [12].

Double ended colour scales are obtained by pasting together two monotonically increasing scales. Their advantage is a clear visual differentiation between low, middle and high values [8]. The *rainbow colour scale* is defined by the horseshoe shaped boundary of the CIE colour model and contains all fully saturated colours. Rheingans points out that it is potentially misleading since the brightest colour (yellow) is in the middle [13]. The *heated-object scale* from Pizer and Zimmermann increases monotonically with brightness from black through red, orange and yellow to white [13]. Its main advantage is the association of colours with high and low values (temperatures). The *optimal colour scales* from Levkowitz and Herman maximizes the number of distinct perceived colours along the scale and increases monotonically with both brightness and RGB components [12]. The authors report that this scale was preferable to the heated object scale when identifying features in medical images.

Textures are used to create visual richness without adding geometry. Van Wijk suggest that texture in data visualization is best used to symbolize global and quantitative information rather than local and qualitative information [19]. Treinish is quoted in [10] as saying that the eye is more responsive to changes in texture than colour. Textures are therefore useful as a redundant cue for shape discrimination. Healey reports that texture and color can only be combined if the texture has a strong textual salience [8].

The shape of an icon can encode three dimensions by scaling it in the coordinate directions (e.g., tensor ellipsoids). Additional information can be represented by its orientation and using other shape related attributes such as curvature and "bumps". The fact that rotated unfamiliar shapes are perceived as different indicates that icons encoding directional information should be simple and familiar to the audience. Shape perception can be improved using lighting, lightness and colour differences, texture, shadows, and contours (both explicit and subjective ones). The principles of Gestalt perception might be important in the design of visualization icons since it has been shown that well-organized, good figures in the Gestalt sense are more easily remembered and make fewer demands on cognitive resources [16].

3.2. Combining Visualization Icons

Visualization icons can be combined into convey containing more information than can be obtained from individual icons [10]. Additional information may exist in the form of correlation between multiple variables or as higher-order visual information (Gestalt).

Correlation between related data sets is perceived most easily when similar visualization icons are used [10]. Perception can be further improved by employing multiple visualization techniques simultaneously for the same data [13].

Gestalt concepts are exploited in the visualization of data by Laidlaw et al. who use densely-arranged normalized tensor ellipsoids in order to obtain a texture-like representation of a diffusion tensor field which improves the perception of features and field properties [11].

In contrast to correlated variables unrelated variables are best displayed using orthogonal (independent) visual attributes such as shape, colour, movement, and texture. Many visualization icons already utilize several visual attributes so extra care has to be taken when combining them. When multiple types of visualization icons are used simultaneously they must be visually distinguishable. Discrimination is achieved by careful use of different shape types, colours and textures. In general it has been shown that the brain can handle at most seven unrelated elements [10]. Note that different visualization icons can also be used to display the same data in order to reinforce information or to highlight different aspects of the data (explicit redundancy).

The effectiveness of visualization icons is influenced by the chosen background. The background can be used to highlight and support features in the image and can be used to provide supplementary information and 3D perspective [10]. Keller and Keller recommend that the background of a visualization should have a neutral (unsaturated) colour with good contrast to the foreground [10]. The authors further recommend the use of a horizontal (portrait) view since it corresponds to the normal field of vision. 3D scenes should be oriented so that important features are in the foreground and not covered by other scene components [10].

3.3. Increasing the Effectiveness of a Visualization

A general approach for the creation of an effective visualization is given by the "Natural Scene Paradigm" which is based on our ability to immediately perceive complex information in a natural scene. Implementing this paradigm involves clear 3D structures and data being associated with recognizable properties of objects. More concrete techniques for improving perception and understanding are shape cues, contextual cues and annotations.

Shape cues are used to improve the perception of the 3D geometry of a scene. Two major classes of shape cues exist: illumination and explicit redundancies. The single most important shape cue is diffuse illumination with shadows and highlights also being important. Use of illumination can be problematic since it influences the perception of colour (e.g., if colour mapping is used). Explicit redundancies include emphasizing the silhouette curves (figure-ground boundary) and contour curves (depth discontinuities) and the use of mirrors.

Contextual cues are used to improve perception by enabling the brain to relate abstract visualization icons to a familiar objects or properties. Examples of contextual cues are coastlines, bounding boxes, and model outlines which improve the perception of positional information. Motion blur is used to indicate velocities. Simple contextual cues to make date more readable include numbered scales, grid lines, and abstract objects to suggest value and relationships (see [18]).

Annotations are used to identify features and to explain relationships. Examples are legends, labels, and markers. Legends should be comprehensive, informative and draw attention to important features in the data set [1] Even though word recognition involves low level visual perception higher order processing tasks such as detection of letters, spelling patterns, syllables, and phonological codes are performed independent of the visual system [17]. This might indicate that careful addition of text and symbols can improve the perception of a visualization without degrading the cognition of other visual information. Overuse of textual information must be avoided, though, since it leads to visual cluttering and information obstruction [18].

The perception of a visualization is improved by allowing user interaction such as paning, detail zoom, fish-eye views and cut-away (clipping) techniques. Advanced 3D interaction is accomplished using immersive environments.

4. Conclusion

We have presented a visualization schema which extends the traditional visualization pipeline by a visual interpretation step consisting of visual perception and cognition. Whereas the traditional approach represents the encoding of data into visual attributes, visual interpretation represents a decoding of visual attributes. In order to create visualization data or subsets of data must be mapped onto visual attributes. We suggested a classification of visual attributes according to information accuracy, information dimension and spatial requirement. This classification can be used as basis for mapping data into visual attributes. The visualization process can be simplified by choosing standardized visualization icons for the data or subsets of it. Care must be taken to ensure that different visual attributes representing the icons do not interfere with each other. We provided a set of guidelines for selecting suitable visualization icons, for combing different visualization icons, and for increasing the effectiveness of a visualization. It is our hope that this work will enable the reader to create more effective and efficient visualizations of scientific data sets.

References

[1] William S. Cleveland. *The elements of graphing data*. Murray Hill, N.J. : AT&T Bell Laboratories, 1985.

[2] Donna J. Cox. Using the supercomputer to visualize higher dimensions: An artist's contribution to scientific visualization. *Leonardo*, 22:233 – 242, 1988.

[3] Jules B. Davidoff. *Cognition through color*. MIT Press, Cambridge, Mass., 1991.

[4] Dr. Betty Edwards. Drawing on the right side of the brain, 2000. Course notes #37, SIGGRAPH 2000.

[5] James A. Ferweda. Fundamentals of spatial vision, 1998. Applications of visual perception in computer graphics, Course #32, SIGGRAPH '98, 1-27.

[6] Georges G. Grinstein and Haim Levkowitz, editors. *Perceptual Issues in Visualization*. Springer Verlag, Berlin, New York, 1995. Proceedings of the IFIP Workshop on Perceptual Issues in Visualization, 23-24 October, 1993, San Jose, California.

[7] Robert B. Haber and David A. McNabb. Visualization idioms: A conceptual model for scientific visualization. In Gregory M. Nielson, Bruce Shriver, and Larry J. Rosenblum, editors, *Visualization in Scientific Computing*, pages 74 – 93. IEEE Computer Society Press, Los Alamitos, California, 1990.

[8] Christopher Healey, Victoria Interrante, and Penny Rheingans. Fundamental issues of visual perception for effective image generation, 1999. Course notes #6, SIGGRAPH 1999.

[9] Glyn W. Humphreys, editor. *Understanding vision : an interdisciplinary perspective*. Blackwell, Oxford, UK ; Cambridge, USA, 1992.

[10] Peter R. Keller and Mary M. Keller. *Visual Cues - Practical Data Visualization*. IEEE Computer Society Press, Los Alamitos, CA, 1993.

[11] David H. Laidlaw, Eric T. Ahrens, David Kremers, and Carol Readhead. Visualizing diffusion tensor images of the mouse spinal cord. In David Ebert, Hans Hagen, and Holly Rushmeier, editors, *Proceedings of Visualization '98*, pages 127 – 134. IEEE, Computer Society Press, October 1998.

[12] Haim Levkowitz and Gabor T. Herman. Color scales for image data. *IEEE Computer Graphics and Applications*, 12(1):72 – 80, January 1992.

[13] Penny Rheingans and Chris Landreth. Perceptual principles of visualization. In Georges G. Grinstein and Haim Levkowitz, editors, *Perceptual Issues in Visualization*, pages 59 – 73, Berlin, New York, 1995. Springer Verlag. Proceedings of the IFIP Workshop on Perceptual Issues in Visualization, 23-24 October, 1993, San Jose, California.

[14] P. K. Robertson and J. F. O'Callaghan. The generation of color sequences for univariate and bivariate mapping. *IEEE Computer Graphics and Applications*, 6(2):24 – 32, February 1986.

[15] James C. Rodger and Roger A. Browse. Choosing rendering parameters for effective communication of 3D shape. *IEEE Computer Graphics and Applications*, 20(2):20–28, March 2000.

[16] Harvey Richard Schiffman. *Sensation and Perception: An Integrated Approach*. John Wiley & Sons, 4th edition edition, 1996.

[17] Kathryn T. Spoehr and Stephen W. Lehmkuhle. *Visual Information Processing*. W. H. Freeman and Company, 1982.

[18] Edward R. Tufte. *The Visual Display of Quantitative Information*. The Graphics Press, Cheshire, Connecticut, 1983.

[19] Jarke J. van Wijk. Spot noise: Texture synthesis for data visualization. In T. W. Sederberg, editor, *Computer Graphics (SIGGRAPH '91 Proceedings)*, volume 25, pages 309 – 318, July 1991.