Reviewing Data Visualization: an Analytical Taxonomical Study

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Abstract

This paper presents an analytical taxonomy that can suitably describe, rather than simply classify, techniques for data presentation. Unlike previous works, we do not consider particular aspects of visualization techniques, but their mechanisms and foundational vision perception. Instead of just adjusting visualization research to a classification system, our aim is to better understand its process. For doing so, we depart from elementary concepts to reach a model that can describe how visualization techniques work and how they convey meaning.

1 Introduction

The large volume of data sets produced in all kinds of human activities motivates the quest for more efficient ways to explore and understand information. The benefits of such understanding reflect in business advantages, more accurate diagnosis, finer engineering and more refined conclusions in a general sense. Computer graphics aided techniques have been researched and implemented in order to provide improved mechanisms for exploring stored data. These efforts are generically known as (data) Visualization, which provides faster and user-friendlier mechanisms for data analysis, because the user draws on his/her comprehension immediately as graphical information comes up to his/her vision.

Several classification schemes have been proposed for visualization techniques, each one focusing on some aspect of the visualization process. However, many questions remain unanswered. What are the building blocks of a visual exploration scene? How interaction mechanisms relate to these facts? These are core issues for implementing and evaluating visualization systems. In this work, we discuss these issues and analytically find answers to them based on the very mechanisms of the visualization techniques and on visual perception theory.

In this paper we discuss the subjective nature of visualization by proposing a discrete model that can better explain how visualization scenes are composed and formed, and how their constituent parts contribute to visual comprehension. We revisit visual analysis proposing a perspective where visualization scenes are considered as a set of components each of which passive of discrete consideration. This discussion is organized as follows. Section 2 reviews former taxonomies from the literature, section 3 presents the basic components of visualization techniques, used as elements for our proposed taxonomy. Section 4 delineates the descriptive taxonomy itself, while section 5 explains how interaction techniques fit into the proposed framework. Finally, Section 6 presents a brief discussion and concludes the paper.

2 Related Work

One of the most referenced taxonomies for Visualization, and well suited to academic purposes, is the one proposed by Keim [13]. It maps visualization techniques within a three dimensional space defined by the following discrete axes: the data type to be visualized (one, two, multi-dimensional, text/web, hierarchies/graphs and algorithm/software), the visualization technique (standard 2D/3D, geometrical, iconic, dense pixel and stacked), and the interaction/distortion technique applied (standard, projection, filtering, zoom, distortion and link & brush). This taxonomy is suitable to quickly reference and categorize visualization techniques, but it is not adequate to explain their mechanisms.

A simpler taxonomy was earlier presented by Schneiderman [27]. It delineates a pair wise system based on a set of data types to be explored, and on a set of exploratory tasks to be carried out by the analyst. This taxonomy, known

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as task (overview, zoom, filter, details-on-demand, relate, history and extract) by data type (one, two, three, multi-dimensional, tree and network) taxonomy, was pioneer in analytically delineating visualization techniques. The effort provides a good idea of what a given technique is and how it can be used.

Another interesting classification is presented by Chi [4], a quite analytical approach, which details visualization techniques through various properties related to a specific visualization model. The taxonomy embraces data, abstraction, transformation and mapping tasks, presentation and interaction. It determines a complete and extensive descriptive system for analytical purposes.

Tory and Möoller [29] define Scientific Visualization and Information Visualization, respectively, as continuous ([one, two, three, multi-dimensional] *versus* [scalar, vector, tense, multi-variate]) and discrete (two, three, multi-dimensional and graph & tree) classes, according to the intuitive perception of their visual modeling. Wiss and Carr [34] describe a cognitive based taxonomy that considers attention, abstraction and (interaction) affordance in order to discus 3-D techniques. Unlike a classification system, this taxonomy can be seen as a guide to "dissect" the subjective nature of visualization techniques.

In the following discussion we also analyze visualization techniques according to a classification scheme but, differently, we concentrate on basic characteristics common to every visually informative scene. We benefit from empirical observations of how data translates to space, that is, how it is *spatialized* and we consider characteristics proposed in visual perception theory (position, shape and color), which determines how pre-attentive features can stimulate our visual system.

3 Components of Visualization Techniques

Visualization can be understood as data represented visually. That is, it takes advantage of *spatialization* to allow data to be visually/spatially perceived and it relies on *visual stimuli* to represent data itens or data attributes/characteristics. Based on these facts an overview of our taxonomy model is presented in Figure 1, which depicts its basic components and their possible classes, further detailed in this text.

3.1 Spatialization

Spatialization of data refers to its transformation from a raw format that is difficult to interpret into a visible spatial format. In fact, Rohrer *et al.* [25] state that visualizing the non-visual requires mapping the abstract into a physical form, and Rhyne *et al.* [23] differentiate Scientific visualization and Information visualization based on whether the spatialization mechanism is given or chosen, respectively. We considered these arguments to analyze spatialization and verified that visualization techniques can be grouped based on how they are mapped into the visual/spatial domain.

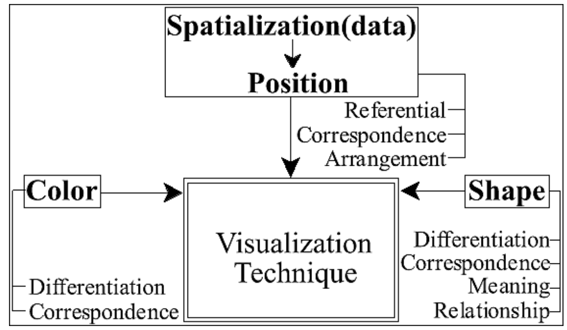

Figure 1. Taxonomy model based on spatialization and visual stimuli. The central rectangle represents visualization scenes. Around the visualization scene are its components: spatialization(position), shape and color together with their possible classes.

3.2 Pre-attentive Visual Stimuli

Semiotic theory is the study of signs and how they convey meaning. According to semiotic theory, the visual process is comprised of two phases, the parallel extraction of low-level properties (called pre-attentive processing) followed by a sequential goal-oriented slower phase. Pre-attentive processing plays a crucial role in promoting visualization's major gain, that is, improved and faster data comprehension [30].

Specifically, pre-attentive processing refers to what can be visually identified prior to conscious attention. Essentially, it determines which visual objects are instantly and effortlessly brought to our attention. The work described by Ware [32] identifies the categories of visual features that are pre-attentively processed. Position (2D position, stereoscopic depth, convex/concave shading), Shape (line orientation, length, width and line collinearity, size, curvature, spatial grouping, added marks, numerosity) and Color (hue, saturation) are considered and, according to Pylyshyn *et al* [21], specialized areas of the brain exist to process each of them (Figure 2). Actually this is true for everything we see, for what we can ask three questions: where is it? what is its shape? and what color is it?

4 Proposed Taxonomy

Visualizing data demands a maximization of just noticeable differences. To satisfy this need, visualizations rely on pre-

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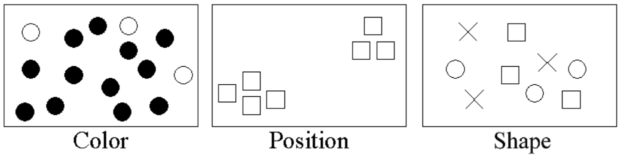

Figure 2. Pre-attentive visual stimuli.

attentive stimuli - characteristics inherent to visual/spatial entities. Therefore, the data must first be mapped to the spatial domain (spatialized) in order to be pre-attentively perceived. Our taxonomy thus focuses on the spatialization process and on the pre-attentive stimuli that are employed by visualization techniques.

4.1 Spatialization

In this section we identify a set of procedures for data spatialization: Structure exposition, Projection, Patterned positioning and Reproduction. In the following section we present the pre-attentive stimuli that complete the requisites to describe a data visualization.

• *Structure exposition*: data can embed intrinsic structures, such as hierarchies or relationship networks (graph-like), that embody a considerable part of the data significance. This class comprises visualization techniques that rely on methods to adjust data presentation so that the underlying data structure can be visually perceived. Examples are the TreeMap technique [28], illustrated in Figure 3(a), and force directed graph layouts [8], such as the one illustrated in Figure 3(b);

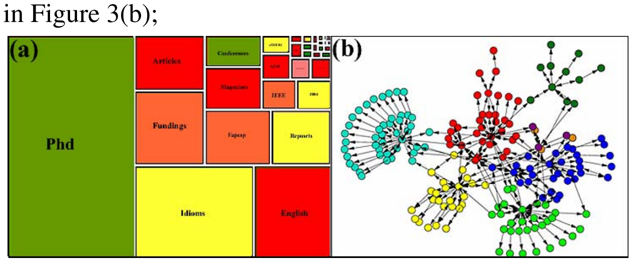

Figure 3. (a) TreeMap structure exposition. *Position:* **hierarchical arrangement;** *shape:* **correspondence (size proportionality);** *color:* **discrete differentiation. (b) Force directed structure exposition.** *Position:* **relational arrangement;** *shape:* **meaningful (arrowed) lines;** *color:* **discrete differentiation.**

• *Patterned*: this is the simplest positioning procedure, with the set of individual data items arranged sequentially (ordered or not) according to one or more directions, linear, circular or according to specific patterns.

Patterned techniques tend to fully populate the projection area and sometimes are referred to as dense pixel displays. Examples include Pixel Bar Charts [15], showed in Figure 4(a), pie charts (circular disposition), depicted in 4(b) and pixel oriented techniques in general [12].

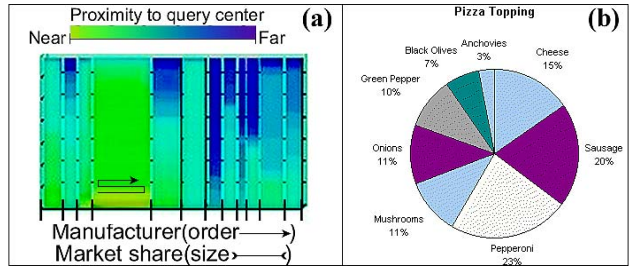

Figure 4. (a) Pixel Bar Charts. *Position:* **manufacturers mapped in horizontal sequence and clients (pixels) mapped according to a patterned positioning;** *shape:* **correspondence (size);** *color:* **continuous correspondence. (b) Pie chart.** *Position:* **each slice maps a different pizza ingredient;** *shape:* **correspondence (size);** *color:* **discrete differentiation.**

Notice that the simple approach of Patterned positioning restricts the presentation of data, which is tipically depicted with shape and size encoding, as in Figures 4(a), 4(b) and 10(c). Keim's pixel-oriented techniques are an exception, in that they use just color, and no shape encoding, to present the data items, which are positioned according to elaborated patterned sequences [14].

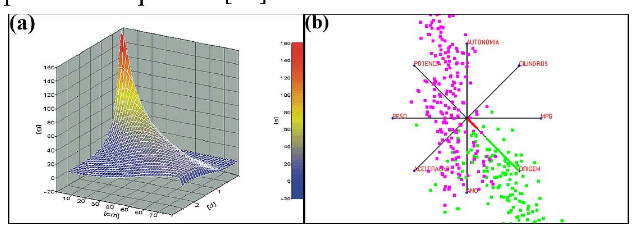

Figure 5. 3D functional plotting. *Position:* **referential (axes);** *shape:* **math surface displays relationship among points; meaningful axes and labels;** *color:* **continuous correspondence. (b) Star Coordinates 2D projection of 8-dimensional data.** *Position:* **referential;** *shape:* **meaningful axes and labels;** *color:* **discrete differentiation.**

• *Projection*: stands for a data display modeled by the representation of functional variables. That is, the position of a data item is defined by either a well-known or an implicit mathematical function. In a projection, the information given is magnitude and not order, as in a patterned spatialization. Examples are Parallel Coordinates (one projection per data dimension), Star Coordinates [11] and conventional graph plots, as illustrated in Figure 5;

• *Reproduction*: data positioning is known beforehand and is determined by the spatialization of the system from where data were collected, as exemplified in Figures 6(a) and 6(b).

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In reproduction, the data inherits positioning from its original source. Usually, specific algorithms [6] are required to identify the data positioning based on its implicit physical structure; other algorithms are used to simplify intractable volumes and/or to derive other features later represented for example as color, glyphs or streamlines.

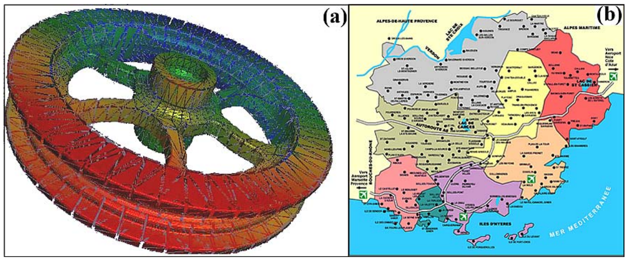

Figure 6. (a) Rendered dataset. *Position:* **referential (surface shape as reference);** *shape:* **meaningful object;** *color:* **continuous correspondence. (b) Geographical map.** *Position:* **referential (background map as reference);** *shape:* **meaningful airport and road identifiers;** *color* **discrete differentiation.** (b) reproduced with permission granted by S.G. Eick.

Reproduction can be seen as a special case of projection where no explicit projection function is given - compare Figures 5(a) and 6(a). Instead, the data positioning derives from the observed phenomenon and it is part of the data. Therefore, projection and reproduction are characterized by considerably different methodologies that confer them distinct classifications, namely, explicit projection and implicit projection (rendering).

4.2 Pre-attentive Stimuli

In this section we analyze well-known visualization techniques in order to empirically identify how attributes Position, Shape and Color are used to express information.

4.2.1 Position

Position is the primary component for pre-attention perception in visualization scenes and it is strictly related to the spatialization process. So, while spatialization is the cornerstone for enabling visual data analysis (as it maps data to the visual/spatial domain), it also dictates the mechanism for pre-attentive positional perception. Thus, positional pre-attention occurs in the form of Arrangement, Correspondence and Referential, explained in the following paragraphs. These classes derive, respectively, from spatializations Structure Exposition, Patterned and Projection/Reproduction.

- *Structure Exposition* → *Arrangement*: specific arrangements can depict structure, hierarchy or some other global property. Without an explicit referential, information is perceived locally through individual inter-positioning of elements and/or globally through a scene overview. For instance, TreeMap (Figure 3(a)) presents the hierarchy of the data items, and a graph layout (Figure 3(b)) presents network information.
- *Patterned* → *Correspondence*: the position of an item, either discrete or continuous, determines its corresponding characteristic without demanding a reference. For example, see Figure 10(b) where each of the four line positions maps one data attribute. Other examples are Parallel Coordinates and Table Lens [22], techniques that define an horizontal sequence for placing data attributes;
- *Projection* → *Referential*: this is the most obvious relation between spatialization and positional pre-attention. Projections have a supporting function whose intervals define referential scales suited to analogical comprehension.
- *Reproduction* → *Referential*: the position of an element, discrete or continuous, is given relative to an explicit reference, such as a geographical map (Figure 6(b)), a meaningful shape (Figure 7(a)) or a set of axes (Figure 7(b));

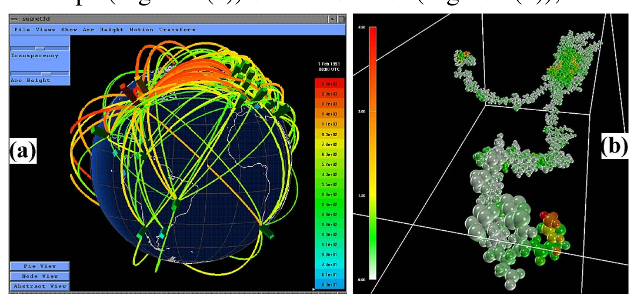

Figure 7. (a) *Position*: **referential (globe as reference);** *shape*: **relationship (curved lines), proportional correspondence (pillars size) and meaning (globe);** *color*: **discrete correspondence. (b)** *Position*: **referential (parallelepiped as reference);** *shape*: **meaning (chemical molecules);** *color*: **continuous correspondence.** Images reproduced with permission granted by S.G. Eick.

We observe that spatialization based on *Reproduction* can yield all the three kinds of positional pre-attention: arrangement, correspondence or referential. This is a consequence of the image characteristics being predetermined from the source being reproduced, which may bear any of these characteristics naturally. However, the most common occurrence is referential pre-attention, to which we limit our exposition.

4.2.2 Shape

We argued so far that a limited number of spatialization procedures is at the core of visualization techniques, and

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that these spatialization procedures dictate the positional pre-attentive stimulus. Nevertheless, after spatializing the data one still needs to choose their shape and color, other pre-attentive stimuli. In this and the following sections we investigate how shape and color contribute to visual perception. In particular, the Shape stimulus embraces the largest number of possibilities to express information: Differentiation, Correspondence, Meaning and/or Relationship.

• *Differentiation*: the shape displayed discriminates the items for further interpretation, as in Figures 8(a), 9(a) and 10(a);

• *Correspondence*: discrete (Figure 8(a)) or continuous (Figure 8(b)), each noticeable shape corresponds to one informative feature. Proportion (variable sizing) is the most used variation for this practice;

• *Meaning*: the shape displayed carries meaning, such as an arrow, a face or a complex shape (e.g. text), whose comprehension may depend on user's knowledge and previous experience, as depicted in Figures 7(b) and 8(b);

• *Relationship*: shapes, such as lines, contours or surfaces, denote the relationship between a set of data items, e.g., in Parallel Coordinates, 3D plots and paths in general, illustrated in Figures 5(a) and 7(a).

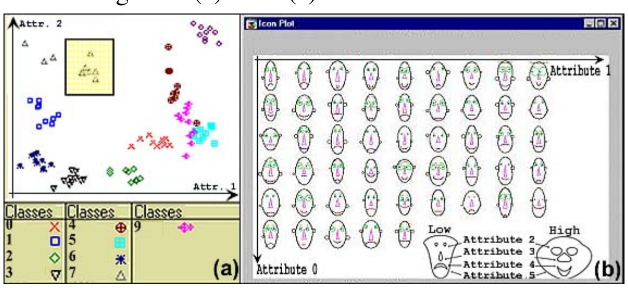

Figure 8. (a) *Position*: **referential (axes as reference);** *shape*: **discrete correspondence and differentiation (square);** *color*: **discrete correspondence. (b)** *Position*: **referential (axes as reference);** *shape*: **continuous correspondence (size and curvature);** *color*: **discrete differentiation.**

4.2.3 Color

After applying a spatialization procedure, which leads to positional clues for perceiving information, and after choosing a shape to convey additional meaning, color is the third pre-attentive stimulus to be considered. Color conveys information by Differentiation and/or Correspondence of data items:

• *Differentiation*: colors have no specific data correspondence, they just depict equality (or inequality) of some data characteristic, as it may be observed in the visualizations depicted in Figures 9(a) and 9(b). The coloring of the items, either discrete or continuous, is data dependent or user input dependent;

• *Correspondence*: discrete or continuous, as observed in Figures 7(a) and (b). In the discrete case each noticeable color maps one informative feature, usually a class, a level, a stratum or some predefined correspondence. In the continuous case, the variation of tones maps a set of continuous data values.

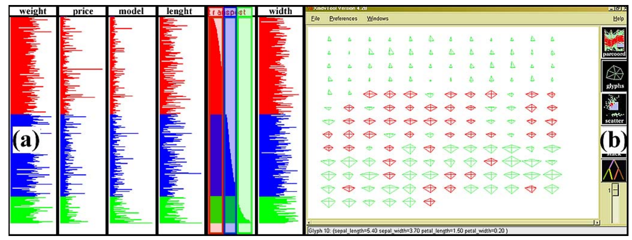

Figure 9. (a) *Position*: **correspondence for attribute order and attribute values;** *shape*: **line size correspondence (all columns) and differentiation (in the 5th column shape indicates selection);** *color*: **discrete differentiation. (b)** *Position*: **referential (window as a Euclidean plane) and correspondence through the circular positioning of the inner sticks of each glyph;** *shape*: **differentiation determined by the contour around each glyph and proportional correspondence for the inner sticks;** *color*: **discrete differentiation.** (b) created with XmdvTool [31].

4.3 Hybridism and Subspace Visualizations

In the process of creating a visualization, it is possible to subdivide the available space into disjoint regions and, then, apply another spatialization process to each subspace. Figure 10(a), for example, shows a grid in which star glyphs are spatialized. Similarly, Figure 10(b) shows a focused star glyph in which sticks are positioned according to a different spatialization procedure. Figure 10(c) demonstrates the relative positioning of the glyphs in the star glyph and, finally, Figure 10(d) shows a focused stick that represents the magnitude of the third attribute of the (hypothetical) jth item.

A similar approach is applied in techniques such as Dimensional Stacking [17], Worlds-within-Worlds [7], Circle Segments [1], Pixel Bar Charts [15] and the so-called iconic techniques in general. Multiple spatialization cycles allow improved space utilization and result in more complex visualization techniques. Moreover, they define hybrid approaches for composing visualizations that allow for the vast number of techniques found in visualization literature. In such compositions, pre-attention occurs as a function of the visualization focus. Such understanding, coupled with

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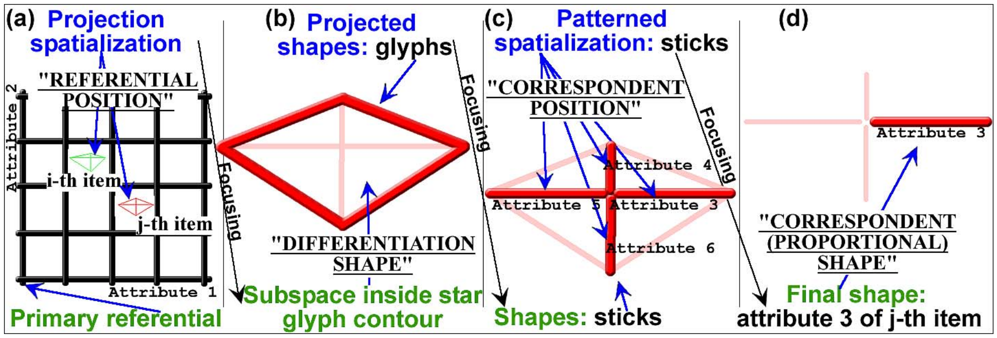

Figure 10. Two spatialization cycles applied in generating a visualization. (a) Projection of star glyphs. (b) Star glyph focused. (c) Arrangement within a glyph. (d) Attribute information as a proportional shape.

our taxonomical system, can provide additional guidance on new thoughts for data visualization.

5 Interaction Techniques

Interaction is an important component for visualization techniques but, differently from former works, we do not incorporate interaction to our taxonomy. In fact, we chose to handle visualization and interaction as disjoint concepts. However, interaction and visual applications present a notable synergy. Therefore, we must clarify the role of interaction techniques in the visualization scene. We define two conditions for identifying an interaction technique:

1. An interaction technique must enable a user to define/redefine the visualization by modifying the characteristics of pre-attentive stimuli;

2. An interaction technique, with appropriate adaptations, must be applicable to any visualization technique.

The first condition arises from the direct assumption that interaction techniques alter the state of a computational application. In the case of a visualization scene, its basic components (the pre-attentive stimuli) must be altered. The second condition arises from the need of having interaction techniques that are well defined, which directs us towards generality. An interaction technique, then, must be applicable to any visualization technique, even if not efficiently. We identify the following interaction paradigms:

• *Parametric*: the visualization is redefined, visually (e.g., scrollbar) or textually (e.g., type-in), by modifying position, shape or color parameters. One could mention as examples, the hierarchical Parallel Coordinates (visual) mechanism described by Fua *et al* [9] and Keim's [12] query-dependent pixel displays that conform to a textual query system;

• *View transformation*: this interaction adds physical touch to the visualization scene, whose shape (size) and position can be changed through scale, rotation, translation and/or zoom, not necessarily all of them, as in the FastmapDB tool [2];

• *Filtering*: a user is allowed to visually select a subset of items that, through pre-attentive factors such as color (brushing) and shape (selection contour), will be promptly differentiated for user perception. Detailed studies are presented by Martin and Ward [19];

• *Details-on-demand*: detailed information about the data that generated a particular visual entity can be retrieved at any moment and presented in the scene. As an example we refer to the interaction (not the presentation) of Table Lens visualization, which permits to retrieve the data that originated a given graphical item and present it in textual (shape) form;

• *Distortion*: allows visualizations to be projected so that different perspectives (positions) can be observed and defined simultaneously. Classical examples are the Perspective Wall [18] and Fish-eye Views [26].

The well-known Link & Brush (co-plots) technique does not satisfy our conditions. It is an application dependent automation that can be implemented only when brushing and multiple visualization techniques share a visualization environment.

6 Conclusions

We illustrate the proposed taxonomy in Table 1, which shows the categorization of some well-known visualization techniques. In proposing this taxonomy we focused on generalizing the rationale of how visualization scenes are engendered and how they are presented to our cognitive system. Such a general characterization results in a taxonomy that does not rely on specific details on how techniques op-

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Table 1. Examples of spatialization-pre-attention analysis

Visualization Technique	*Spatialization→Position*	*Shape*	*Color (usual)*	*Prospective Interaction*
Chernoff Faces [3]	Projection→Referential, Patterned→Correspondence	Correspondence, Differentiation	-	Filtering
Dimensional Stacking [17]	Projection→Referential	-	Differentiation	Filtering
Parallel Coordinates [10]	Projection→Referential, Patterned→Correspondence	Relationship	Differentiation	Filtering
Scatter Plots [5]	Projection→Referential	-	Differentiation	Filtering
Star Coordinates [11]	Projection→Referential, Patterned→Correspondence	-	Differentiation	View transformation, Details-on-demand
Stick Figures [20]	Projection→Referential, Patterned→Correspondence	Differentiation, Correspondence	Differentiation	Filtering
Worlds-within-Worlds [7]	Projection→Referential	-	-	View transformation
Bar Chart	Projection→Referential	Correspondence	Correspondence	Filtering, Parametric
Pixel Bar Charts [15]	Projection→Referential, Patterned→Correspondence	Correspondence	Correspondence	Filtering, Parametric
Circle Segments [1]	Patterned→Correspondence	-	Correspondence	Details-on-demand
Keim's Pixel Oriented [12]	Patterned→Correspondence	-	Differentiation	Filtering, Parametric
Pie Chart	Patterned→Correspondence	Correspondence	Correspondence	Filtering, Parametric
Table Lens [22]	Patterned→Correspondence, Projection→Referential	Correspondence	Differentiation	Filtering, Details-on-demand
Cone Tree [24]	Structure Exposition→Arrangement	Relationship	Differentiation	View transformation, Details-on-demand
Hyperbolic Tree [16]	Structure Exposition→Arrangement	Relationship	Differentiation	View transformation, Details-on-demand
Treemaps [28]	Structure Exposition→Arrangement	Correspondence	Differentiation	Filtering, Details-on-demand
Geographical Maps	Reproduction→Referential	Differentiation, Correspondence	Differentiation	Filtering, Details-on-demand
Vector Visualization	Reproduction→Referential	Meaning, Correspondence	Differentiation, Correspondence	View transformation
Direct Volume Rendering [33]	Reproduction→Referential	Meaning	Differentiation, Correspondence	View transformation

erate. Rather, it considers their fundamental constituent parts: how they perform spatialization and how they employ pre-attentive stimuli to convey meaning. Our claim is that such an approach is required to gain a general understanding of the visualization process.

Existing taxonomies categorize techniques based on diverse and detailed information on how techniques perform a visual mapping. This diversity and detailing (refer to Section 2) include, e.g., axes arrangement ("stacked techniques"), specific representational patterns ("iconic and pixel-oriented techniques"), predisposition of representativeness ("network and tree techniques"), dimensionality ("2D/3D techniques") and interaction ("static/dynamic techniques"). Although such approaches can suitably describe the set of available techniques, they lack analytical power because the core constituents of the techniques are diffused within the taxonomical structure.

Our approach results in an extensible taxonomy that can accommodate new techniques as, in fact, any technique will rely on common foundational basis. We see this taxonomy as a starting point for fomenting further discussions and thoughts on how visualization techniques operate and how we can improve our understanding of them. Hopefully, it can contribute to give us better grounds for design, evaluation and implementation of techniques in the future.

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