The spatial-perceptual design space: a new comprehension for data visualization†

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Abstract
We revisit the design space of visualizations aiming at identifying and relating its components. In this sense, we establish a model to examine the process through which visualizations become expressive for users. This model has lead us to a taxonomy oriented to the human visual perception. The essence of this taxonomy provides natural criteria in order to delineate a novel understanding for the design space of visualizations. From such understanding, we elaborate a model for generalized design. The model poses an intuitive comprehension for the visualization design space departing from fundamental pre-attentive stimuli and from perceptual phenomena. The paper is presented as a survey, its structure introduces an alternative conceptual organization for the space of techniques concerning visual analysis.

Keywords: Data visualization; information visualization; taxonomy; design space; visualization model

Introduction and related work
Research on data visualization aims at providing improved mechanisms for information exploration and analysis, offering faster and friendlier – if compared to traditional analytical approaches – techniques to assist on data comprehension. This is possible because an analyst can, with reduced effort, augment her/his comprehension of a data set when interacting through graphical representations.

Visualization, as it occurs with any research field, will benefit from a conceptual framework to organize methods and techniques in a unified comprehensionspace, that is, a delimited space of possibilities where one can navigate through the constituent variables without losing her/his referential locus.

Following this assumption, recent publications about the next steps for visualization research have addressed the importance of the topics dealt in the present work. Thomas and Cook,1 recommend the need to ‘Conduct research to formally define design spaces that capture different classes of visualizations’; Johnson et al.2 state, among their long-term recommendations, the need to systematically explore the design space of visual representations; and Chaomei3 observes the need to understand elementary perceptual-cognitive tasks based on a substantial amount of empirical evidence.

Several works in the literature have sought to accomplish such goals, either from an analytical or from a taxonomical perspective. The analytical approaches listed in Table 1 (a) strive to empirically identify the ultimate elements of visualizations and to draw their relationship. Bertin4 presents eight visual variables: the two planar dimensions x and y plus
six retinal variables: size, value, grain, color, orientation, and shape. In order to support automatic design, Cleveland and McGill\textsuperscript{5} and Mackinlay\textsuperscript{6} define empirical studies over simple data visualizations aiming at stating the usefulness of specific visual patterns. Card \textit{et al.}\textsuperscript{7} follow the theories of Bertin introducing concepts about the importance of the spatial substrate and how it can be used.

Taxonomical approaches, listed in Table 1(b), aim at empirically identifying common characteristics pertaining to existing visualization techniques in order to propose class-oriented organizations. Keim\textsuperscript{8} concentrates on high-level visual patterns in order to define a space of possibilities intuitive for users. Shneiderman\textsuperscript{9} focuses on the possible combinations of visualization practices and interaction. Chi\textsuperscript{10} describes visualization techniques focusing on data and its transformations. Bugajska\textsuperscript{13,14} thoroughly treats the topic of spatial design for abstract visualization. She proposes a holistic approach in sharing expertise among visual design, computer science, and social fields of study. Tweedie\textsuperscript{15} suggests a number of recommendations for design in a work oriented to guidelines. In this work, we focus on organizing the visual features of design from a perceptual-cognitive perspective.

Former analytical and taxonomical approaches focus mainly on high-level components of visualizations: data types, visual patterns, visual appearance, user tasks, and interaction mechanisms. These works brought significant contribution to visualization design and understanding, but they have overlooked the process through which visualizations become expressive for users. This process relates to how data translate into visual stimuli and to how these stimuli translate into reasoning. Our claim in the present work is that the consideration of this particular process contributes to a better understanding of visual data presentations. With this consideration in mind, we organize the space of visualizations both taxonomically and analytically (design space definition).

We observe that, distinctly from works oriented to design guidelines (what to do), analytical works focusing on design space theories (what can be done) aim at providing improved conceptual organizations so that design-related
Figure 1 Example of preattention. Identifying the number of ‘4’ symbols (22 in total) is easier when the symbols are emphasized (B), than when they are not (A). Adapted from Ware.17

Figure 2 Pre-attentive visual stimuli.

activities can be better engendered. Regarding the important topic of design guidelines, MacEachren16 presents a complete book that extensively reviews methods for data presentation at the same time that he evaluates their adequacy. MacEachren states that the meaning of a map is not absolute but a product of the society and its culture. He also states that the way information is mentally represented determines how groups and societies can develop a consensus about data representation. This consensus, in the realm of data visualization, is the object of the theoretical and empirical investigation that supports our work.

In the area of design space theories, our initial considerations are based on the work by Card et al.,7 who identify the elements of visualizations. Card et al. start from the assumption that visualizations are limited to the spatial substrate (position), to marks and to graphical properties pertaining to these marks. Such graphical properties are what Bertin4 defines as retinal properties. Ware 17 distinguishes the retinal properties proposed by Bertin as visual patterns defined either by shape or by color. In line with these former studies, we consider visualizations as being composed of three fundamental components: position, shape, and color. Each of these components conveys visual perceptual cues, which we refer to as visual perceptions. The observation of these phenomena is formalized in a model named Visual Expression Process, which grounds this work.

The remaining of this paper is organized as follows. The next section introduces the fundamentals of this work, presents the Visual Expression Process, and delineates our research line. The subsequent section guides our initial ideas by proposing the Spatial-Perceptual Taxonomy. The fourth section exemplifies our concepts and discusses further possibilities. Fifth and sixth sections, respectively, explain the Spatial-Perceptual Design Space and the role of interaction in the proposed framework. Following, seventh section proposes a unified model for visualization, named Visualization Machine, which integrates all the proposed concepts. The penultimate section presents further analytical examples and the final section concludes the paper.

Fundamentals

In the present work we define two levels of abstraction for the practice of visualization: design of visualization techniques and design of visualization systems. While the design of techniques is concerned to how a visual representation should be structured and look like, the design of visualization systems is concerned to the aspects of data processing, of visualization techniques and of interaction. We emphasize that the scope of this work applies essentially to the topic of visualization techniques. Nevertheless, for the sake of completeness, we touch the topic of visualization systems (processing + visualization + interaction) discussing how and where our theory relates to systematization. In this section, initially, we introduce the underlying knowledge and the basic definitions central to the development of our ideas.

Semiotics and pre-attentive visual stimuli

Semiotic Theory, from Vision Science, is the study of signs and their ability to convey meaning. According to this theory, the visual process comprises two phases, namely, the parallel extraction of low-level properties (called pre-attentive processing), followed by a slower detailed scan. The first phase, pre-attentive processing, plays a crucial role in promoting the major benefit of visualizations, that is, improved and faster data comprehension.18 Meanwhile, the second phase addresses conventional reading practices that do not contribute towards faster visual cognition. In this sense, Ware17 states that understanding what is processed pre-attentively, see Figure 1, is probably the most important contribution that Vision Science can bring to data visualization.

Pre-attentive processing refers to whatever can be visually identified through unconscious processes. As such, it determines which visual objects are instantly and effortlessly brought to our attention.

As depicted in Figure 2, Ware17 identifies the categories of visual features that are pre-attentively processed. His study considers Position, Shape, and Color – besides the animation of each of these three factors. In this line, Pylyshyn et al.19 affirm that there are specialized areas of
the brain to process each of these stimuli. Actually, the position–shape–color perception is true for everything we see. At any moment and for anything on which we focus our eyes, we can ask three questions: where is it? what is its shape?, what color is it?

For visualizations to be effective, they must build on pre-attentive features in order to maximize the number of just noticeable differences. In fact, although visual processes are not limited to pre-attention, visualization design is supposedly oriented to maximize design-specific pre-attentive effects. That is, there are many graphical properties, but just a limited number of them can be used for visual analysis. Accordingly, in this research we assume that visualizations are composed of features that are potentially or desirably pre-attentive. Following this conception, pre-attention effectiveness may vary, or even be absent, depending on the data and on the particular design.

Spatial schemas, achieved via data spatializations, are the main graphic representations. Data spatialization refers to the transformation of data into a visible/spatial format. Straightly, it is possible to conclude that the spatial positioning, dictated by spatialization processes, is what promotes positional pre-attention. In their state-of-the-art work, Card et al. refer to the spatial substrate as the most fundamental aspect of a visual structure, being the first decision in the visualization design. In fact, Rohrer et al. state that visualizing the non-visual requires mapping the abstract into a physical form. Rhyme et al. distinguishes Scientific Visualization and Information Visualization based on whether the spatialization mechanism is given or chosen, respectively. Spatialization is the fundamental element to enable visual data analysis, at the same time that it dictates the characteristics of the pre-attentive positional perception.

The visual expression process

The Visual Expression Process is a scheme of how visualizations improve useful knowledge acquisition. The diagram in Figure 3 describes the process, which departs from pre-attentive visual stimuli – the presence of a data set is naturally assumed – and culminates in data interpretation. The key elements of such process are: the pre-attentive stimuli used to conceive visualizations, the concept of visual perception, and the interpretation factor. The model is now examined in order to grasp its structure, in search for a new strategy for the visualization science.

Pre-attentive stimuli and visual patterns

Our initial assumption is that visualizations are composed of three pre-attentive stimuli – position, shape, and color – presented in section ‘Semiotics and pre-attentive visual stimuli’ and depicted at the left-hand side of Figure 3. For each of them, a set of visual patterns may be employed for the visualization design. Such patterns include, but are not limited to:

- **position**: 1D/2D/3D position, stereoscopic depth;
- **shape**: line, area, volume, form, orientation, length, width, collinearity, size, curvature, marks, numerosity, convex/concave;
- **color**: hue, saturation, brightness.

**Visual perceptions** Visual perceptions designate the limited number of user-related phenomena that are fired by the pre-attentive stimuli composing a visual presentation, see Figure 3. They are observable even if the user has no

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**Figure 3** The visual expression process.

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knowledge about the underlying data and, therefore, they are an inherent component of the visualization practice.

Visual perceptions seem to be the natural features that any user tries to identify when interpreting a visualization scene. If they are not found by the user, the pipeline outlined in Figure 3 is broken and the visual expression process is interrupted. Owing to their importance, we have surveyed the occurrence of visual perceptions in visualization literature. We found a limited set and, by empirical observation, we verified that this set is recurrent in visualization techniques. We also observed that each visual perception is fired by one or by multiple pre-attentive stimuli, having either a discrete or continuous nature.

In the work by Bertin, and also observed by Bowman and Card et al., one can identify two occurrences of visual perceptions: extended expression (which we call correspondence) and differentiation of marks. Mackinlay states that the perception of relationships comes from visual patterns that remind of the notion of connectivity. Besides these three visual perceptions, namely correspondence, differentiation, and connectivity, we have also identified: arrangement, for perceptions that arise from group positional configurations (Gestalt principles); and meaning, for perceptions that draw on resemblance to previous knowledge and/or expertise. The list of visual perceptions we have identified includes, but it is not limited to:

- **correspondence**: each position/shape/color establishes a distinct correspondence with respect to some referential map. The need for an explicit visual map or for an implicit mental map is assumed. Examples of visual maps include axes, geographical maps, shape/color dictionaries, and position/shape/color variation ranges. Examples of mental maps include known orderings and shape metaphors;
- **differentiation**: each position/shape/color discriminates one or more graphical items. Differentiation is the simplest visual perception and can be understood as a kind of correspondence in which the user creates a temporary mental map in memory;
- **connectivity**: shapes, mainly edges, that convey information about relationships;
- **arrangement**: Gestalt principles of organization. Positional placements (similarity, continuity, closure, proximity, symmetry, and figure/background) that convey information about group properties, for example clusters and structural cues;
- **meaning**: positions/shapes/colors whose interpretation relies on the expertise of the user or on previous knowledge. Meaning can be understood as a kind of correspondence established from visual entities to concepts retained in the long-term memory of the user. Something is perceived as meaningful if its significance extends beyond the context of the visualization.

Other visual perceptions could possibly be identified, as for example, textual labels, textures, and enclosure, as proposed by Mackinlay. However, we do not include them in the above list. Textual labels may be considered compositions of shapes expressing perceptions of meaning or differentiation. Enclosure derives from shape differentiation and Gestalt principles. As for textures, Kimchi reviews the literature of Vision Science stating that textures have been interpreted as similarity-based groupings of shapes. For the visualization science, textures are somewhat at the boundary between shape expression (the individuation of the shapes in the texture) and color expression (the grouped shapes).

### Interpretations

Interpretations refer to conclusions, inferences, or deductions produced with the aid of the visualization scene in conjunction with the knowledge of the data domain. As depicted in Figure 3, the user interpretation of a given visualization occurs as a consequence of her/his visual perception. Data visualization may be more or less effective in providing proper interpretations, it depends on the data, on the visualization itself, and on the user. Our understanding is that interpretations include, but are not limited to the following list of concepts: correlation, tendency, classification, relationship, summarization, outlier, cluster, structure, and reading.

### The visual expression process

Figure 3 aggregates the observations made so far into a single process, named **Visual Expression Process**. Three cognitive tasks are involved in this process: conception, observation, and reasoning. The design conception requires establishing how position, shape, and color will be employed for visual stimulation; during observation, visualizations (properly designed) necessarily provide visual perceptions; user reasoning based on the visual perceptions, and on the data domain knowledge, may or may not induce interpretations about the data.

Our view is that the Visual Expression Process is the underlying process behind all visualization techniques. Intuitively, one can say that the visual patterns of position, shape, and color are purely related to the raw data and that, through visual perception, interpretations can be achieved. Interpretations, in turn, are related not to data, but to new information in the context of the application domain.

The arguments we develop in this work apply to empirical observations related to vision processes seeking to maximize perception for data exploration and, as such, they are restricted to the science of Data Visualization – *a priori*, we do not claim that they apply to Vision Science in general.

### Research line

The Visual Expression Process presented in the former section establishes that, given a visualization, two steps are required to produce knowledge: observation of visual
stimuli and reasoning. Between these two steps there is a gap separating visualizations from interpretations. This gap is fulfilled with the concept of Visual Perceptions.

Our thesis is that it is possible to deploy a taxonomical and analytical theory that, while based on visual stimuli, is oriented to visual perceptions. This choice is justified by the observed properties of Visual Perceptions, that:

- are not numerous, in contrast to visual patterns;
- are common to every visualization, in contrast to interpretations;
- can be categorically related to the pre-attentive stimuli, allowing for immediate recognition and association;
- constitute a key element for visual analytical cognition.

These features suggest that a perceptions-oriented study can be more rational than former works mainly oriented to visual patterns (see the first section). Besides the cardinality and ubiquity of perceptions, it is easier to know which interpretations can be achieved from a given perception than from a given visual pattern. It is possible to break a visualization into distinct parts: pre-attentive stimuli of position (spatialization), color and shape that, in turn, derive visual perceptions of correspondence, connectivity, differentiation, arrangement, and meaning. We believe that this analytical course can provide a simpler control of which visual effects are effective, and for what. We use this notion in order to review the visualization science from a non-holist perspective.

The goal of this work is to introduce an alternative organization of concepts, a platform for comprehension and for discrete analysis of visualization techniques. In this sense, in next section the paper starts with the description of a taxonomy that identifies the features that characterize visualization techniques. Following, these features are represented in a space of design possibilities where each set of points corresponds to a taxonomical class. Complementing our theorization, we introduce an ideal model for navigating the design possibilities predicted by our theory.

Contributions
To state the contributions of this work, we compare its principles with the work by Card et al.,7 which is the most cited theory in the topic of visualization design spaces. Compared to Card et al. we make the following observations:

- Distinctly from Card et al., and from most of prior theories, our work is not centered on visual patterns (retinal properties) whose number and diversity raise difficulties for a clear and general analytical view of visualizations. Instead, we argue that a user is more interested on the visual perceptions that she/he can benefit from than on the visual patterns that she/he can use. For example, instead of desiring a set of axes and points, a user would be more interested in observing properties of correspondence that are present (or not) in the data.
- Card et al. affirm that the space can be configured through techniques of composition, alignment, folding, recursion, and overloading. This proposition reveals that, instead of defining a general understanding, the authors tried to exhaustively list the different ways that the space can be occupied in visualization design. This lack of generality prevents the analyses of techniques such as the Star Glyphs and VisImpact.25 Differently, we introduce an alternative comprehension for space utilization, which is closely related to spatialization and to gradual occupation;
- In the same way as for spatial design, interaction is not part of Card et al. theory (nor of many prior theories). Instead, the authors introduce an exhaustive list of observable interactive practices. In their work, there is no relation between the visualization elements and the interaction practices that they identify. In a more general way, our proposition states that interaction mechanisms are natural ways to alter the parameters of the pre-attentive components present in any visualization.

The spatial-perceptual taxonomy
The objective of the following taxonomical study is to improve the comprehension of what are the components of visualizations and how to classify such components from a perceptual-cognitive perspective. Differently from guideline-oriented studies, we do not focus on specific visualization cases. Rather, the discussion fosters a comprehension for the analytical appreciation of the overall visualization practice, independent of usability or adequacy. We start our taxonomy by discussing spatialization followed, in the next sections, by shape and color discussions.

Spatialization
Based on the notion of spatialization, we have verified that visualization techniques can be grouped according to how they are positioned in space. We have identified the following classes: Structure Exposition, Sequencing, Projection, and Reproduction.

- Structure Exposition: Data can embed intrinsic structures, such as hierarchies or relationship networks (graph-like), that embody a considerable part of the data significance. We designate as Structure Exposition the techniques aiming at exposing the data structure. Such techniques rely on methods to adjust the data presentation so that the underlying structure can be visually noticed; they are usually domain specific and attempt to maximize the perception of arrangement. Examples include the TreeMap technique26 (hierarchical recursive positioning), illustrated in Figure 4(A), and force-directed graph layouts27 (iterative positioning), illustrated in Figure 4(B).
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Figure 4 (A) TreeMap Structure Exposition. Position: hierarchical arrangement; shape: continuous correspondence (size proportionality); color: discrete differentiation. (B) Force-directed Structure Exposition. Position: relational arrangement; shape: connection lines and meaningful arrows; color: discrete differentiation.

Figure 5 (A) Pixel Bar Charts – each pixel sequentially maps the transactions of hypothetical manufacturers. Position: discrete correspondence to the map of labels that identify the manufacturers positioned in horizontal Sequence, and continuous correspondence of the transactions (pixels) to the Sequential mental map following the ascending time order declared over the scene; shape: continuous correspondence (width); color: continuous correspondence. (B) Pie chart Sequencing. Position: discrete correspondence to the non-ordered circular Sequence of labels; shape: continuous correspondence (area); color: discrete differentiation.

• Sequencing: The simplest positioning procedure. It works by placing the data set in a sequential positioning, typically following the overall equation:

$$(x_{i+1}, y_{i+1}, z_{i+1}) = f(x_i, y_i, z_i)$$

that is, the position occupied by a particular data item only depends on the position of the preceding item. Sequential spatializations adopt linear, circular or more elaborated patterns that constitute the positional mapping of the visualization. These mappings can fire visual perceptions of differentiation or correspondence. Differentiation is intrinsic to position, while correspondence is achieved when a map is provided. Sequential spatializations typically adopt mental or visual positional maps. Mental mappings are based on a declared order, as illustrated in Figure 5(A). Visual mappings are based on a positional map that explicitly identifies each position, as illustrated in Figure 5(b).

Sequential positioning techniques tend to fully populate the display area and some of them are referred to as dense pixel displays. The pixel-oriented techniques proposed by Keim28 are well-known examples of Sequential positioning. They use just color and no shape encoding to present the data items positioned in sequential patterns. Pixel Bar Charts29 is a variation of such techniques, it relies on two spatialization cycles in order to benefit from size encoding.

• Projection: Stands for a data display modeled by functional variables. The position of a data item is defined by a mathematical function (either explicit or implicit) that generates a set of positional marks representing the data. The marks state perception of correspondence to the axes used as positional maps. At the same time, the discrete set of positional marks can compose, via implicit or explicit interpolation, lines, areas, surfaces, or volumes...
that induce perception of positional meaning. An axial reference is required for spatializations based on Projection that, in general, take the format:

\[(x_i, y_i, z_i) = f(d_{i,0}, d_{i,1}, \ldots, d_{i,n-1})\]  \hspace{1cm} (2)

where \(d_{i,j}\) is the \(j\)th attribute of the \(i\)th data item and \(n\) is the data set dimensionality. Examples include Parallel Coordinates (one Projection per data dimension), conventional plots and Star Coordinates,\(^3\) as illustrated in Figures 6(A) and (B);

- **Reproduction**: Data positioning is known beforehand, having been determined by the original spatialization of the system/phenomenon that generated the data. Ideally, the visualization and the observed phenomenon should define:

\[(x', y', z') = R(x, y, z)\]  \hspace{1cm} (3)

where \(R\) is a function that takes as input a set of real-world coordinates and outputs 3D rendering coordinates. Figure 7 illustrates two examples. Usually, specific algorithms\(^3\) are required to identify the data positioning based on the implicit physical structure of the data. Other algorithms may be employed to simplify intractable volumes and/or to derive additional features represented as colors, glyphs, or streamlines. Reproduction can be seen as a special case of Projection, where the projection function is unknown; instead, the data positioning derives from the observed phenomenon, as for volume rendering and geographical charts.

In Reproduction, similarly to Projections, data are mapped to positional marks that, via interpolation, can compose lines, areas, surfaces, or volumes – compare Figures 6(A) and 7(A). Differently from Projections, the positional reference (e.g., axes or background) is optional – see Figure 7(A) – and, usually, it is assumed that the graphical items are embedded in a Euclidean space.
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Figure 8  (A) Projection of classified items. Position: continuous correspondence to the projection axes; shape: discrete correspondence, and differentiation (selection square); color: none. (B) Chernoff faces Projection. Position: continuous correspondence to the projection axes, and discrete correspondence to the features mapped to the human face; shape: continuous correspondence (size and curvature); color: none.

Shape

We have argued so far that a limited number of spatialization procedures is at the core of visualization techniques, and that these procedures dictate the positional pre-attentive stimulus. Nevertheless, after data spatialization, one still needs to decide how shape and color will compose the visualization. In particular, the Shape stimulus embraces the largest number of possibilities for visual perception:

- **Correspondence**: Discrete or continuous, each noticeable shape has a specific correspondence in a shape mapping. If no mapping is given, the intuitive mapping ‘bigger size – higher magnitude’ is typically assumed. Figure 8 exemplifies the discrete (A) and the continuous cases (B).
- **Differentiation**: The displayed shapes simply discriminate the items for further interpretation, as in Figures 8(A) and 13(A);
- **Connectivity**: Line segments that denote connectivity between graphical items as, for example, in the Parallel Coordinates, in node–link graph visualization (illustrated in Figure 4(B)), and in the visualization in Figure 9(A);
- **Meaning**: Shapes such as arrows, faces, or other complex formats (e.g. text) carry meaning whose interpretation relies on user knowledge, experience, and culture, as depicted in Figures 7(B) and 9(B).

At the border line between shape and position, shapes (arrows, crosses, triangles, faces, borders, etc.) are considered part of the visualization design only if they were explicitly selected to integrate it. Shapes not explicitly selected are in fact positional marks that may, via implicit or explicit interpolation, constitute lines, areas, surfaces or volumes, possibly with a certain complexity level that indirectly defines, perception of positional meaning instead of shape meaning.

Color

After applying a spatialization procedure, which leads to positional cues, and after choosing shape expressivity to convey additional meaning, color is the third pre-attentive stimulus. Color conveys information through the following visual perceptions:

- **Correspondence**: Discrete or continuous. In the discrete case, each noticeable color defines a correspondence to a color mapping (see Figure 9(A)). In the continuous case, the variation of tones maps to a continuous range of values, as shown in Figure 9(B).
- **Differentiation**: Colors bear no specific correspondence, they just depict an idea of equality (or inequality) of graphical entities, as it may be observed in the examples shown in Figures 5(B) and 7(B).
- **Meaning**: The displayed colors carry meaning. For example, red for alert and specific materials resemblance (as in some textured colorings). Comprehension depends on the knowledge, experience and culture of the user.

The Spatial-Perceptual Taxonomy is based on three criteria for classifying visualizations: space, shape, and color. These features define different refinement perspectives for classification: only spatialization, only shape, only color and the combinations of these aspects. In the next sections, considering the possibility of multiple cycles of spatializations, we deepen into the notions of our taxonomy by defining its space of possibilities (the Spatial-Perceptual Design Space) and by defining a model for navigating this space (the Visualization Machine).
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Figure 9  (A) Globe-map-based reproduction. Position: the reproduced points state continuous correspondence to the globe; shape: connectivity (curved lines), and correspondence to pillar size; color: discrete correspondence. (B) Chemical structure Reproduction. Position: the reproduced points state correspondence to the enclosing parallelepiped, and meaning according to the chemical structure achieved via interpolation of the points; shape: not given/chosen (explicit interpolation); color: continuous correspondence. Images reproduced with permission granted by Stephen G. Eick.

Figure 10  The formation hierarchy for the Spatial-Perceptual Taxonomy.

The taxonomy formation hierarchy
The proposed taxonomy classifies visualization techniques considering criteria that derive from the very constitution of the techniques. Hence, such criteria embrace classes that reflect constitutional aspects. Owing to its descriptive – rather than only classificatory – properties and due to its multiple criteria nature, the Spatial-Perceptual Taxonomy comes to an amplitude that does not permit a readable enumeration of its classes, either in a tree or in a tabular format. For this reason, in Figure 10, we present the formation hierarchy that permits to envision the classes of our classification scheme.

Analytical examples and multiple spatializations

Analytical examples
Following, we illustrate our taxonomy by inspecting the components of two typical visualization techniques. First, let us consider a classical pie chart – see Figure 11 – along with a fictitious data set. For this example, the visualization design starts by adopting a circular Sequential spatialization along with a positional mapping of meaningful shapes (labels). The labels are used to state correspondence for each chart position. In a second step, shape (area) correspondence is applied to provide extra encoding. The result
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exhibits slices whose sizes are proportional to the values of attribute \( X \). As the last step, a discrete coloring is applied for further differentiation. The pie chart is an intuitive and straightforward visualization design. For this reason, one tends to see it as a monolithic visualization, missing its components. Nevertheless, identifying such components may provide clues for new designs or to exploit design variations.

In a second example, the Parallel Coordinates technique is used to illustrate the application of multiple spatialization procedures. We consider a hypothetical data set with four-attribute (\( W, X, Y \) and \( Z \)) records, where attribute \( Y \) is a classification attribute. To start, a Sequential positioning is defined for the names of the attributes. The low dimensionality enables having a positional map where the names of the attributes go along with the initial visualization. Each position corresponds to a specific attribute name. In the second step, the values of each attribute are projected vertically having axes as positional maps. This second spatialization cycle benefits from the empty space in the display area. Note that the spatializations are integrated so that the items placed in the first cycle (attribute names) become a positional reference to the items placed in the second cycle (Projected attribute values). In the next step of the design, shapes (line segments) stating connectivity are employed in order to express which data items are interrelated according to the data set records. The final step uses color encoding in order to differentiate the polylines.

Multiple spatializations

As exemplified in Figure 12, visualizations may show disjoint regions, each with a different spatialization strategy. Another example is shown in Figure 13(A), where one can see the spatialization of star glyphs in a grid according to a Projection of two attributes. Figure 13(B) focuses on one of these glyphs showing the available space within the glyph. Figure 13(C) shows that, within each glyph, the remaining attributes are positioned based on a Sequential spatialization. Finally, Figure 13(D) focuses on a particular stick whose size corresponds to the magnitude of the third attribute of the (hypothetical) \( j \)th item.

Similarly to the examples shown in Figures 12 and 13, multiple spatialization cycles are applied in techniques such as Dimensional Stacking,32 Worlds-within-Worlds,33 Circle Segments,34 Pixel Bar Charts29 and in many of the so-called iconic techniques. Multiple spatialization cycles define hybrid approaches that comprise a vast number of the techniques found in the literature. In such compositions, pre-attention depends on how one focuses on the visualization.

Multiple spatialization cycles is a key factor for the diversity in visualization design. Integrated spatialization cycles allow improved space utilization and result in more complex techniques. In the next sections, we show that such understanding, coupled with our taxonomical system, can provide guidance on new thoughts for visualization. Table 2 presents similar analyses for several visualization techniques widely referenced in the literature. In these case studies, one can perceive that the use of multiple (and possibly heterogeneous) spatializations are common, not to say necessary. It is also possible to see that shape is not always explored, perhaps because of spatial limits. Color, in turn, can always be used without overloading the design framework. Each set of configurations in Table 2 can be understood as a complete characterization according to our taxonomy.
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Based on the Visual Expression Process (section ‘The visual expression process’) it is possible to conceive a Perceptual Space, as illustrated in Figure 14(A), that describes the expressiveness of visualization techniques. The axes of this space correspond to the available possibilities of the basic visualization elements. As so, a visualization technique is defined in terms of its parameters regarding the choice of position, shape and color, each one cast to a subset of the visual perceptions we have identified: correspondence, differentiation, connectivity, arrangement, and meaning.

This idea may be further refined following the Taxonomy introduced in the third section. The Perceptual Space (Figure 14(A)), then, becomes the Spatial-Perceptual Space, illustrated in Figure 14(B). This new scheme assumes that positional perception is dictated by the spatialization processes. In this space, the positional dimension becomes the spatialization dimension, according to how we describe this concept in the third section.

Finally, we consider the possibility of multiple spatialization cycles, as discussed in section ‘Multiple spatializations’, to depict what we call Spatial-Perceptual Design Space. The design process now becomes a series of space filling cycles that follows the space/perception design and proceeds until all the available space is occupied. In Figure 14(C) we present the Spatial-Perceptual Design Space for techniques whose conception adopts multiple spatialization cycles.

The Spatial-Perceptual Design Space presents the notion of visualization design in an intuitive Euclidean space, where each point (or set of points) addresses a possible configuration. In the next sections we also observe that, besides the design of visualization techniques, complete visualization systems embody two other steps: pre-exhibition data processing and interaction.

Interaction techniques

The scope that we have chosen to explore in this work is the definition of a design space oriented to visual expressivity. Accordingly, we have focused on the visual appeal of sole data visualization techniques, rather than on the operational features of complete visualization systems (data management-visualization-interaction). Unlike previous works, interaction is not a component of our theory; rather, it rises as a natural product of the proposed concepts.

In this section, we clarify the role of interaction techniques under the light of the concepts we have introduced. We observe that this work does not intend to determine how interaction can be used in the visualization design: our aim is only to determine where does interaction fit our theory. Interaction is a much wider field of research, thus we believe that separating interaction from visualization helps to keep the conceptual model clear. We establish two conditions to identify an interaction technique:

1. An interaction technique must enable a user to define/redefine the visualization by modifying pre-attentive stimuli.
2. An interaction technique, with appropriate adaptations, must be applicable to any visualization technique, in an efficient way or not.

The first condition is a direct consequence of the assumption that interaction techniques change 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 derives from the need to have a well-defined, yet general, concept. Interaction techniques, then, must be applicable to any visualization technique, even if not efficiently. In the current literature, we identify the following interaction paradigms satisfying our criteria:

- **Parametric**: The visualization is indirectly redefined through mechanisms that reflect on new parameters for position, shape or color; visually (e.g., scrollbar) or textually (e.g., type-in). An example is the Hierarchical Brushing mechanism described by Fua et al.\(^47\)
- **View transformation**: This interaction allows changing shape (size) and position of a visual scene through scale, rotation, translation, and/or zoom, as in FastmapDB.\(^48\)
Table 2 Examples of spatial-perceptual analyses considering common settings for classical techniques

| Visualization technique | Spatialization | Shape | Color | Prospective interaction |
|-------------------------|----------------|-------|-------|-------------------------|
| Chernoff faces          | Projection, Sequencing | Differentiation, Correspondence | —     | Filtering               |
| Dimensional stacking    | Multiple Projection | —     | Differentiation | Filtering               |
| Parallel coordinates    | Sequencing, Multiple Projection | Connectivity | Differentiation | Filtering               |
| Scatter plots           | Multiple Projection | —     | Differentiation | Filtering               |
| Star coordinates        | Projection | —     | Differentiation | Filtering               |
| Stick figures           | Projection, Multiple Sequencing | Differentiation, Correspondence | Differentiation | Filtering               |
| Worlds-within-Worlds    | Multiple Projection | —     | Differentiation | View transformation     |
| Parallel coordinates/star Glyphs | Multiple Sequencing, Multiple Projection | Connectivity | Differentiation | Filtering, parametric  |
| Flow map layout         | Projection | Correspondence, | Correspondence | Details-on-demand       |
| Bar chart               | Projection | Correspondence, | Correspondence | Filtering, Parametric   |
| Pixel bar charts        | Projection, Multiple Sequencing | Correspondence | Correspondence | Filtering, Parametric   |
| Circle segments         | Multiple Sequencing | Differentiation | Correspondence | Filtering, Details-on-demand |
| Pixel-oriented techniques by Keim | Multiple Sequencing | —     | Correspondence | Filtering, Parametric, Details-on-demand |
| Pie chart               | Sequencing | Correspondence, | Differentiation | Filtering, Parametric   |
| Table lens              | Sequencing, Multiple Sequencing | Correspondence | Differentiation | Filtering, Details-on-demand |
| InterRing               | Structure Exposition | Correspondence | Correspondence | View transformation, Details-on-demand |
| Cone tree               | Structure Exposition | Connectivity | Differentiation | View transformation, Details-on-demand |
| Hyperbolic tree         | Structure Exposition | Connectivity | Differentiation | View transformation, Details-on-demand |
| Treemaps                | Structure Exposition | Correspondence | Differentiation | Filtering, Details-on-demand |
| Voronoi Tree-maps       | Structure Exposition | Correspondence | Correspondence | Filtering, Details-on-demand |
| Geographical maps       | Reproduction with referential | Differentiation, Meaning | Differentiation | View transformation, Details-on-demand |
| Vector visualization    | Reproduction | Meaning, Correspondence | Correspondence | View transformation     |
| Direct volume rendering | Reproduction | Not given/chosen (explicit interpolation) | Correspondence | View transformation     |

- **Filtering**: One can visually select a subset of items that will be promptly differentiated for perception by changing pre-attentive properties such as color (brushing) and shape (selection contour). Detailed studies are presented by Martin and Ward.49
- **Details-on-demand**: Detailed information about the data that generated a particular visual entity can be retrieved for exhibition. As an example, we refer to the interaction used in the Table Lens visualization technique – it allows retrieving the data that originated a given graphical item and present it using textual (shape) visual patterns.
- **Distortion**: Allows visualizations to be projected so that different perspectives (positions) can be observed and defined simultaneously. Classical examples are the Perspective Wall50 and the Fisheye Views.51
The well-known Link & Brush (co-plots) technique does not satisfy the conditions to be considered an interaction technique. Link & Brush is more like a design-dependent automation. It is based on the possibility of integrating multiple spatializations so that interaction tasks applied to one of the spatializations reflect on the others. One could generalize Link & Brush and think of Link & View Transformation (e.g., synchronized panning), Link & Parameters (e.g., parameters multicasting), Link & Distort (e.g., simultaneous perspective alteration), and so forth. Such concepts are referred in the literature under the term Coordinated Multiple Views.

The visualization machine model

Facing visualizations from the perspective of the proposed theory allows conceiving an ideal generalized visualization mechanism. This is illustrated in Figure 15, which shows a model integrating the Spatial-Perceptual concepts described so far.

The Visualization Machine, described next, is not a finalized scheme, but a seminal idea. Its principle is the reduction of the visualization design in such a way that, theoretically, it could be mechanically performed as a designer navigates through the possibilities predicted by our theory. In this context, the frame over which the Visualization Machine evolves is in the format of a hierarchy of possibilities. The branches of these hierarchy lead to compositions based on spatialization, shape, and color.

A top-down model

Our model states that a visualization is achieved by carrying out a course of steps that starts with the spatialization of a set of data items. The initial spatialization then undergoes shape and color encodings and may be followed by other spatialization cycles. In the model illustrated in Figure 15, each step of the visualization design defines a decision point (black circles in the figure) that will iteratively generate a visualization that conforms to the choices of the user (designer). A careful look reveals that the Visualization Machine is a model that supports user navigation through the space defined by the Spatial-Perceptual Design Space presented in the fifth section.

A pre-exhibition data processing step complements the overall design process. Pre-exhibition processing is not in the main scope of this work; however, as the Visualization Machine embodies systematization, we have added it to our conceptual model. This step occurs before spatialization, when data are usually processed to permit management and mapping. Pre-exhibition processing is executed using database support and includes operations such as reduction of the number of data items, selection of attributes, dimensionality reduction, summary...
computation, data items classification, data mining operations, to name a few. In many domains, pre-exhibition data processing is a necessary step before conceiving the visualization.

**Pools of parameters**
In our systematization, the design steps are assisted by pools of methods concerning spatialization, shape, and color expression. The pools represent sets of known methods that can be used to conceive patterns for visual ensembles. User intervention permits to use these pools to define parameters for each of the steps, from pre-exhibition data processing to coloring, allowing the user to choose the procedures and the patterns that best match her/his needs. Along the text we have shown several examples of design that apply to well-known visualization techniques. The constituents of such designs exemplify the repertory of the pools of parameters that we propose.

**Supervision/intervention**
The choice of parameters defined via user intervention demands supervision, both automatic and user provided. A supervision module is depicted at the left-hand side of the schema in Figure 15. Supervision is aimed at verifying the parameters for each step of the design process in order to determine what are the choices that can be applied in the current and in the subsequent steps. In the current step, supervision is supposed to consider the current user choice in order to select the methods that can be properly used from the current pool of parameters. For the subsequent steps, supervision is supposed to filter out choices that might lead to bad designs. For example, due to the limited space in conventional displays, it is not reasonable to choose a Sequential spatialization of a million items and then to choose a shape correspondence in the next step. More important, the supervision module is also cast to collect data about the spatialization cycles. This is necessary in order to monitor the available space to be used by further spatialization cycles, and to detect and offer possibilities to integrate multiple spatializations. Such integration is essential for the conception of more complex techniques that benefit from multiple spatializations. For example, it can promote link-like automation, so that interaction parameters are multicast to more than one spatialization; or it can promote coordinated spatializations, so that the items in different display areas follow the same ordering.

**Interaction**
The definition of interaction introduced in the previous section states that any interaction technique fits any
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Figure 16 Design process for the classic Star Glyphs technique according to the visualization machine model.

| Component                     | Parameter                      | Visualization |
|-------------------------------|-------------------------------|---------------|
| spatialization: projection    | attributes 1 and 2            |               |
| spatialization: circular      | attributes 3 to 7             |               |
| sequencing                    |                               |               |
| shape: correspondence and     | sticks with proportional     |               |
| differentiation               | shape and contour             |               |
| color: differentiation        | emphasis on highest           |               |
| interaction: filtering        | pool of colors                |               |

In order to instantiate visualization configurations. This possibility contrasts with the current paradigm, in which visualizations are limited to implementations following specific, rigid designs.

Together with the Spatial-Perceptual Taxonomy and Design Space, the Visualization Machine defines a set of concepts for an alternative understanding of data visualization design. The model is supposed to be an incremental framework where new implementations can be combined with already existing modules. We believe this is the overall line through which visualization science will evolve, probably reaching a unified convergence. Following we describe our design process in two examples.

Further analytical examples

Star Glyphs

As a first example, we go through the design process of the classic Star Glyphs technique, illustrated in Figure 16. The design conception starts by adopting a spatial Projection according to attributes, say, 1 and 2; no shape; no color. These first decisions define a complete cycle over the visualization. Thus, any interaction technique should be readily applicable in the Visualization Machine model, see right-hand side in Figure 15. Of course, the availability and adaptation of each interaction paradigm will follow the nature of the specific parameters chosen for design. Interaction efficiency reflects the integration of all the selected components.

An expanding system

The Visualization Machine is a system that can create visualizations based on sets of design parameters. It is an environment that manipulates foundational aspects of the visualization science. Under this perspective, visualization research may turn into a discipline that aims at formulating methods of spatialization, shape, and color expression. New methods fitting our model would then be incrementally incorporated in the repository pools. In this scenario, it is possible to think of an incremental environment in which users would apply configuration parameters previously conceived by specialist designers. These parameters would automatically set up the machine stating which methods to use and how to integrate them
Visualization Machine logic. Following, a second cycle takes place. For each Projected data item, and respecting the remaining empty space, we apply a Sequential circular spatialization of attributes 3–7; for shape encoding, we opt for correspondence and choose sticks with proportional shape; we opt for differentiation by connecting the outer extremities in order to draw the contour of the glyphs; for color, we can benefit from differentiation, having the highest value in each dimension emphasized in red. Finally, having two cycles of design, we can benefit from interaction over the first cycle, using filtering over the projected items.

Coordinated parallel bar charts
In this example (see Figure 17), we design a variation of the well-known Parallel Coordinates technique called Coordinated Parallel Bar Charts. Initially we consider a semantically rich hypothetical dataset with four-attribute records (gross domestic product, population, per capita income, and country name). First, like in the Parallel Coordinates technique, we apply a Sequential positioning of the attributes; meaningful shapes (labels) and no color. In a second cycle, the values of each attribute are Projected vertically, having the highest values at the lower bounds of the axes. At this point we observe that it is possible to benefit from correspondence perception using shape proportionality. This decision creates the appearance of a sequence of bar charts presentation. In the last steps, we choose relationship via shape encoding (polylines) and color differentiation much like in the classic Parallel Coordinates. The final result is a technique that, besides showing the values of the attributes through positional correspondence, also stresses the distortions that can be observed in the domain of each attribute.

Conclusions
In this paper we have introduced a new comprehensive perspective for the design space of visualizations. To do so, initially we identified the Visual Expression Process in order to delineate a new strategy for analysis. This observation allowed us to concentrate on the expressiveness of visualizations in order to identify their elements. These elements were the basis to conceive the Spatial-Perceptual Taxonomy, which considers visualizations as sets of components that provide a limited number of visual perceptions. This investigation led us to the Spatial-Perceptual Design Space, which aggregates the presented ideas in a single conception. For completeness, we have also discussed how interaction techniques fit into our theory. The proposed taxonomy and design space were finally integrated into a design scheme named Visualization Machine Model. Along the text, to validate our observations, we analytically reviewed a number of designs according to the proposed ideas.

The proposed work is centered on how users perceive visualizations, rather than on which visual patterns are used to build a given visualization. Our approach brings designers closer to the expressive characteristics of visual ensembles. We believe that this theorization can promote a more intuitive understanding of the design process, fostering further research toward a more precise and comprehensive design science.

This work naturally introduces future research lines. The topic of animation applies to all the features studied in this work: space, shape, and color. The study of animation requires an ample understanding of its implications and of the intricacies of its elaboration. In another line, a Spatial-Perceptual study must be carried out at the level of visualization systems so that, expanding our line of analysis beyond visual design, the structuring of complex visualization environments can be envisioned with pre-exhibition data processing, advanced interaction and multiple coordinated views. Finally, the Visualization Machine is a conceptual proposition to illustrate the usability of our theory and to suggest new directions for visualization research. Its feasibility must be traced and drawn in a realization project.

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