Visual Variables in Adaptive Visualizations

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Abstract. Visualizations provide various variables for the adaptation to the usage context and the users. Today's adaptive visualizations make use of various visual variables to order or filter information or visualizations. However, the capabilities of visual variables in context of human information processing and tasks are not comprehensively exploited. This paper discusses the value of the different visual variables providing beneficial and more accurately adapted information visualizations.

Keywords: Adaptive Information Visualizations, Visual Variables, Visualization Tasks

1 Introduction

Information visualization and visual analytics provide valuable techniques for interacting with huge amounts of data and solving information-related tasks. [9] In the recent past, researchers from different disciplines recognized the need for a more human-centered design process in visualizations ([1], [15]). These human-centric thoughts resulted in research and development of adaptive information visualizations (AIV), which consider various contextual aspects to adapt visualizations ([1], [2], [23], [13], [14]). In particular, the user plays an increasing role, with her behavior, pre-knowledge and aptitudes ([15], [23], [1], [13]). For involving users in the visualization adaptation process, various systems were developed and successfully evaluated [1]. Although, the users' behavior was analyzed with various techniques and different modeling approaches, the adaptation capabilities of visual information representation were not comprehensively exploited. The focus of visual adaptation was rather on only one value of the available visual variables. Similar to recommendation systems, filtering [12], selection ([13], [14]) or ordering [2] was adopted to these systems.
This paper investigates the distinguishability of visual variables based on the early definition of Bertin [3]. Further findings from the area of vision perception and various task classifications are investigated to outline the need for the adaptation of both, *layout* and *presentation* as proposed in [18]. We believe that one main question for adaptive visualizations still remains, namely how to adapt the visual representation [6]. The main contribution of this paper is an enhancement and application of cognitive models to the adaptation of visual representations. Observations already showed that the use of various visual variables results in different level of task-solving accuracy [8].

2 Interaction and Tasks in Visualizations

Interaction with visualizations enables the dialog between user and the visual representation of the underlying data. The interactive manipulation of the data, the visual structure or the visual representation provides the ability to solve various tasks and discover insights. The main goal of interactive visual representations still remains the acquisition of knowledge [16]. The term “task” in context of information visualization is often used ambiguously. A dissociation of interactions and tasks in visualizations is rarely performed, whereas the knowledge about the task to be solved with the visualization is of great importance for its design and therewith for the adaptation. We have investigated various task and interaction classifications ([4], [7], [10], [11], [17], [19], [22], [26], [28], [33], [34]) to a find an abstract view on visual tasks for a mapping to the human information processing. Therefore all the tasks and interactions were categorized into three abstract levels: “search”, “explore”, and “analyze”. Figure 1 illustrates the identified high-level tasks and their assigned interactions and subtasks derived from the existing visual task classifications.

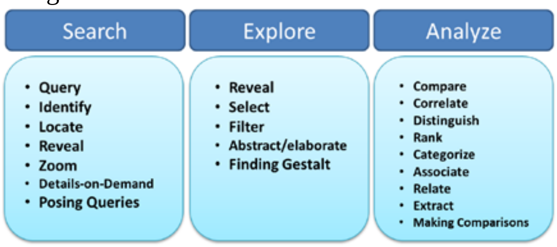

Fig. 1. High-level tasks with assigned subtasks and interactions

3 Visual Variables and Human Perception

The differentiated investigation of visual variables allows a more goal-directed adaptation to users’ needs and tasks. [20] An early definition and differentiation of visual variables was proposed by Bertin [3]. He differentiates between visual variables that use the two dimensions of a plane to encode information through graphical marks and those, which encode information through their relationship above the plane. A graphical mark is defined by basic geometrical elements of points, lines and areas. The position of a mark indicates a meaning between the values of the two dimensions. Marks could be changed through their *size*, *saturation*, *texture*, *color*, *orientation* and *shape*. These features (retinal variables) [27] can further be classified in ordinal, quantitative, selective and associative variables [3].

The second class of Bertin’s visual variables (*imposition*) encodes information through their relationships to each other above the plane. He differentiates this based on how these relationships can be visually illustrated in *diagrams*, *networks*, *maps*, and *symbols*. [3] The main value of Bertin’s classification in the context of this paper is the differentiation between the graphical *layout* and visual (or retinal) variables. The differentiation is of great importance for adapting visualizations, which is also supported by results in cognitive science (e.g., *feature integration theory or guided search model*). However, the established model of Card et al. [5], make use of visual variables (*Visual Structure*) but does not differentiate the layout from presentation. Different and independent studies illustrated a rapid and parallel processing of the retinal variables by the low-level human vision ([24], [25], [29], [30], [31], [32]). The so called "pop-out effect" makes use of the human's parallel vision processing and guides the attention to the related location on the screen [32]. Ware proposes a three-tiered model by considering both the pre-attentive parallel processing and attentive stages of human vision [27]. He subdivides the attentive processing of visual information into a serial stage of *pattern recognition* and a further stage of *sequential goal-directed processing*. [27]. While the pre-attentive stage refers to the retinal variables, the attentive stages (or post-attentive stages) require a serial (or sequential) processing of information, which can be provided by visual information of object relationships over the plane [27]. This aspect of attentive serial processing, in particular by separating the visual retinal variables and layout information was also investigated by Rensink ([20], [21]). In his *coherence theory* and the *triadic architecture* the strict differentiation of *layout* and the low-level retinal variables was proposed in terms of the dynamic generation of a visual representation ([20], [21]). Rensink's *triadic architecture* starts with the low-level vision (pre-attentive) and is generally similar to Ware's model. The most important aspect in this context is the unification of *layout*. Rensink proposes that one important aspect of the scene structure is *layout*, "without regards to visual properties or semantic identity" (p. 36, [20]).

Based on the three introduced models and the results on research of parallel and serial processing we introduce a model for visual adaptation on an abstract level by considering the high-level visual tasks as a foundation for discussing the adaptable variables of visualizations (Figure 2). This is a refined model of the previous work on an adaptive reference model [18] and proposes the use of the different visual variables for adapting visualizations to the users' knowledge and tasks.

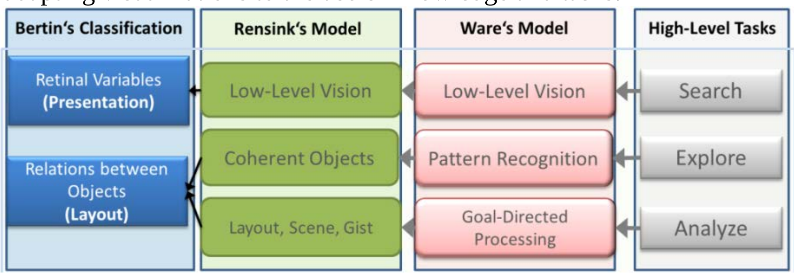

Fig. 2. Model of layout and presentation in adaptive visualizations

4 Conclusions

We introduced various models for differentiating visual variables in context of human information processing and lined out that a separated view on layout (visualization types) and presentation (retinal variables) is important for an accurate and beneficial adaptation of visualizations.

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