Can Physical Visualizations Support Analytical Tasks?

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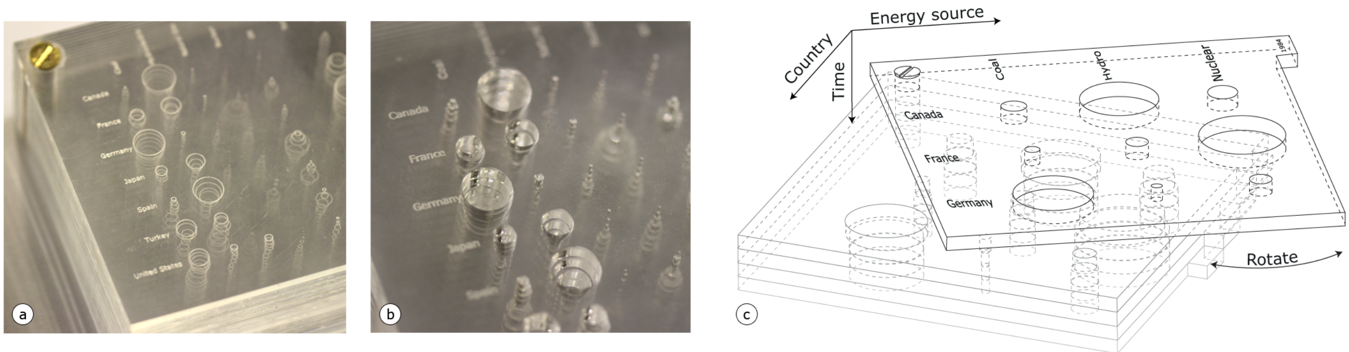

Figure 1: Two alternative physical visualizations, where each data case is represented by an engraved circle (a) or hole (b). The x axis represents energy sources, the y axis countries and the z axis time (c). Each layer can be rotated about time axis.

ABSTRACT

While physical objects have been used to represent information for a long time, physical visualizations only recently started to attract attention from the InfoVis and HCI communities. In this article we present our early experiments in designing physical visualizations for supporting data analysis. Based on Amar's taxonomy of analytical tasks [1] we show that physical visualizations can support a number of analytical activities but that further research is needed to support all activities. Based on our analysis, we propose promising directions for future research.

Keywords: Tangible, Visualization, Physical visualization.

Index Terms: Computing methodologies → Visual analytics.

1 PHYSICAL VISUALIZATIONS

As Jansen and Dragicevic showed with their curated lists[1,2] of physical visualizations (PVs), artists and designers designed and produced a wealth of physical representations of data. They are well suited for playful exploration and stimulate curiosity and awareness [2]. As a physical object that can be explored by all senses, they are less prone to creating information overload and distress [6]. Vande Moere [4] writes that the use of physical materials as a communication medium allows for rich, cultural connotations that evoke user fascination and engagement. He argues that PVs can represent information in pleasant ways and turn data analysis in an engaging and educational experience. While these benefits are widely recognized, the analytic value of physical visualizations remains to be explored [5].

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[1] http://www.aviz.fr/Research/PassivePhysicalVisualizations
[2] http://www.aviz.fr/Research/ActivePhysicalVisualizations

As a starting point for this exploration, we examine to which extent PVs can support established analytical tasks of the InfoViz domain. Based on Amar's taxonomy of analytical tasks [1], we discuss how these tasks are supported, and analyze the benefits and drawbacks of PVs for each of these tasks.

2 CASE STUDY: LAYERED 2D PLOTS

To better understand their properties, we built and experimented with PVs for a range of different datasets and in various form factors. We cut our prototypes from transparent acrylic glass using a laser cutter, which enables rapid prototyping with high precision for creating accurate PVs.

Figure 1 a) and b) show two alternative PVs of a country indicator dataset from Gapminder[3] similar to the datasets used by Jansen et al. [3] (more images of different PVs can be found in our flickr gallery[4]). Data is plotted along 3 dimensions to provide a compact representation. The PV consists of layered 2D plots, in which the x axis represents energy sources, the y axis countries and the z axis (layers) time (see Figure 1 c). Each data case is represented by a hole in the respective layer. The width of this hole represents the percentage of energy production from the respective source by the respective country for a given year. This PV is easy to interpret because it relies on a well-established 2D visualization. Combined with a generic dataset, people were readily able to interpret it. Moreover, it has the unique property of being articulated: Layers can be rotated independently from each other about the time axis. Although the PV we discuss here is only a specific instance of a much larger design space, we use it as a starting point to ground the discussion and offer promising research directions[5].

3 SUPPORTING ANALYTICAL TASKS

We reviewed several taxonomies of analytical task for information visualization [1, 7, 8] and decided to use the taxonomy by Amar et al. [1], because it focuses on user-centered activities rather than on data representation,

[3] http://www.gapminder.com
[4] http://www.tinyurl.com/pv-stusak
[5] See poster and Flickr gallery for more examples.

3.1 Task 1: Retrieve value

Finding the attribute values of specific cases in the data set is fundamental and often constitutes a subtask of other analytical tasks. Our PV allows locating, viewing and grasping all presented values, and physical touch seems to be an essential cognitive aid [3]. Retrieving exact values is also possible with the help of a physical measuring tool, such as a vernier caliper, if the PV was built in the appropriate scale.

3.2 Task 2: Filter

Filtering data based on various criteria is effective in getting further insight into a limited subset of the data. Our visualization allows filtering out specific years by rotating the corresponding layers. It also affords focusing visually on one source/country combination and its changes over time. More efficient filtering methods could be used to highlight only specific elements.

3.3 Task 3: Compute Derived Value

Computing an aggregate numeric representation, such as the average or the sum of specific attributes, is not supported by our PV. It would require sophisticated mechanical construction or digital augmentation, which are promising topics of investigation.

3.4 Task 4: Find Extremum

Finding attributes with maximum or minimum values with our visualization is possible in various ways. Along the time axis, one can easily spot the widest and narrowest layer by looking along the hole across slices. In order to find the maximum value for a given country and year, we need to slide out the respective layer and compare all holes in a source row. This is more difficult visually since the differences between the values can be small, but touching or using rigid objects can also be used for comparisons.

3.5 Task 5: Sort

The PV we built supports sorting along the time axis by loosening the screw and rearranging layers. A specific country/source combination can, for example, be sorted in ascending order by stacking layers according to increasing hole sizes. Sorting along the country and source axes is not supported and would probably require more complex mechanical arrangements, such as Bertin's original data matrices.

3.6 Task 6: Determine Range

The range of an attribute can be understood by looking at all its unique values. Our visualization supports recognizing whether an attribute's range of values is wide or narrow by looking along the respective axis. For example, it is easy to see that the electricity production from nuclear sources in France has a wide range.

3.7 Task 7: Characterize Distribution

The characterization of the distribution of an attribute's values over the data set is limited. Our PV shows well where changes of the values are taking place and whether these are frequent and large or whether in contrast an attribute has many similar values. However identifying distributions is limited by the static arrangement of our physical visualization.

3.8 Task 8: Find Anomalies

Finding outliers or unexpected values is often a good basis for further exploration of a data set. Our PV supports this task well by providing a good overview of the entire data set. Since large changes in size are perceived preattentively by the visual system, outliers within a specific year can efficiently be spotted by a quick look at the respective layer. As another example, there are small changes in electricity production year by year in most countries. A large shift can easily be recognized in the use of nuclear sources by France or in the use of oil sources by Japan in the seventies.

3.9 Task 9: Cluster

Grouping similar items together is only possible along the time axis, because within a layer, values cannot be rearranged. One can focus on specific groups visually and by pointing physically but clustering is quite limited. Dynamic visual highlights or physical rearrangement could enable efficient clustering.

3.10 Task 10: Correlate

Determining useful relationships between the values of different attributes is supported by our PV. For example, it is easy to discover that every country, with the exclusion of Turkey is using nuclear sources of electricity. The fact that Japan shifted their electricity production from coal and hydroelectric to oil in the seventies, can also easily be seen.

4 Summary and Directions for Future Research

As the analysis above shows, many analytic tasks can be supported by PVs and they provide a particularly good overview of the data set. Some tasks require the use of additional tools, e.g., for measuring; others require mechanical manipulation or even disassembling and reassembling the PV. The fact that PVs are three-dimensional objects, which can be visually and haptically explored from all directions, provides a very efficient way to combine visual and physical manipulation to focus on specific dimensions or elements in the data set.

In order to further chart the design space of PVs, researchers can start from established digital visualizations as in our example. A promising field of exploration is the construction of mechanically functioning visualizations, which allow dynamic exploration of a data set. We have shown how a simple rotation axis can already support the analytic tasks of filtering and sorting, and we believe that other tasks, such as relating or the calculation of derived values can be realized by more sophisticated mechanical constructions, possibly involving non-rigid, elastic parts or even liquids. We hope to provide a solid starting point for a more systematic exploration of this fascinating design space.

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