On the Faithfulness of Graph Visualizations

Quan Nguyen*, Peter Eades, and Seok-Hee Hong

School of Information Technologies, University of Sydney, Australia
{qnguyen,peter,sshong}@it.usyd.edu.au

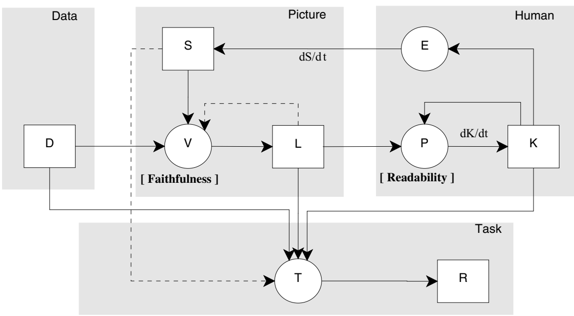
1 Introduction

Graph drawing algorithms developed over the past 30 years aim to produce "readable" pictures of graphs. Here "readability" is measured by *aesthetic criteria*, such as few crossings or few edge bends or small grid drawing area. However, the readability criteria for visualizing graphs, though necessary, are not sufficient for effective graph visualization.

This poster introduces another kind of criterion, generically called "faithfulness". Intuitively, a graph drawing algorithm is "faithful" if it maps different graphs to distinct drawings. Faithfulness criteria are especially relevant for modern methods that handle very large and complex graphs; data reduction or aggregation or generalisation are commonly exercised to enhance readability.

2 Graph Visualization Model

Fig. 1 depicts our general graph visualization model. The model extends the van Wijk's model [7] to include *tasks*, and to handle dynamic graphs and incremental algorithms.



1) Data space D contains from a simple to a time-varying graph with complex attributes. *2*) Specification S includes hardware specifications like screen size. *3*) Layout/image space L consists of graph drawings or structured objects in a multi-dimensional geometric space. *4*) Result space R may contain from a simple true/false to a complex matrix.

Fig. 1. Graph visualization model of the whole knowledge discovery process, from data to visualization to human

The main processes of the model are: *1*) The *visualization process* maps a *data* $d \in D$ to a *layout* (or *"picture"*) $\ell = V(d) \in L$ according to a *specification*

* See our full technical report [6].

W. Didimo and M. Patrignani (Eds.): GD 2012, LNCS 7704, pp. 566–568, 2013.
© Springer-Verlag Berlin Heidelberg 2013

$s \in S$. *2*) The *perception process* maps a picture ℓ to the *knowledge* $k \in K$. The term *knowledge* is sometimes called *insight* or *mental picture*, which is perceived from observation of the picture. *3*) The *task process* T maps a data d, a layout ℓ, and a knowledge k to a *result* $r \in R$. In practice, visualizations are developed for domain-specific *tasks* (e.g., identifying important actors in a social network), and the well-defined *low-level* tasks.

3 Faithfulness Model

A graph visualization is *faithful* if the underlying network data and the visual representation are logically consistent. We distinguish three kinds of faithfulness. *a*) *Information faithfulness* requires that the picture l of data d should contain all the information of the data d, irrespective of tasks. *b*) For *task faithfulness*, a visualization should be accurate enough to correctly perform tasks. *c*) So far as *change faithfulness* is concerned, the change in the picture should be consistent with the change in the original data.

4 Examples

Example 1: Multidimensional Scaling and Force Directed Approaches. The *multidimensional scaling (MDS)* approach [4] takes an input graph and a matrix of *dissimilarities* $\delta_{u,v}$, and aims for a layout l that minimizes the stress of $\sum_{u \neq v} (\delta_{u,v} - d_{u,v})^2$, where $d_{u,v}$ is the actual distance between nodes u and v in layout l. *Force directed algorithms* [1] have a similar flavour, but view the problem as finding equilibrium in a system of forces.

With *task faithfulness*, the more similar the nodes, the closer they are in the picture. For *change faithfulness*, MDS methods have been used extensively in dynamic settings, using stress to preserve the mental map. These measures, however, aim for the mental map preservation rather than change faithfulness. For example, they do *not* ensure that if the change in the graph is *large*, then the change in the layout is *large*.

Example 2: Edge Bundling has been extensively investigated to reduce visual clutter in graph visualizations. Edge bundling seems to increase *task readability* for some tasks; e.g., the classic bundling of US airline networks eases the identification of the main hubs and flight corridors. Yet some readability metrics are sacrificed; e.g., the number of bends is increased, making path tracing difficult.

Regarding faithfulness, edge bundling reduces information faithfulness: as the more edges are bundled, the harder to reconstruct the original data from a bundled layout. As *task faithfulness* is concerned, most bundling methods are built around the compatibility between pairs of edges, e.g., force-directed edge bundling (FDEB) method [2] and its variants [2,3,5]. We have experimented with some metrics for assessing how well the geometries of bundled edges conform with the compatibility metric. We have also attempted with the following hypotheses: *1*) FDEB methods are task-faithful; *2*) FDEB methods are *more* task-faithful when using *more* control points per edge.

References

1. Fruchterman, T.M.J., Reingold, E.M.: Graph drawing by force-directed placement. Softw. Pract. Exper. 21(11), 1129–1164 (1991)
2. Holten, D., van Wijk, J.J.: Force-directed edge bundling for graph visualization. Computer Graphics Forum 28(3), 983–990 (2009)
3. Kienreich, W., Seifert, C.: An application of edge bundling techniques to the visualization of media analysis results. In: InfoVis, pp. 375–380. IEEE (2010)
4. Kruskal, J.: Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. Psychometrika 29(1), 1–27 (1964)
5. Nguyen, Q., Hong, S.-H., Eades, P.: TGI-EB: A New Framework for Edge Bundling Integrating Topology, Geometry and Importance. In: van Kreveld, M., Speckmann, B. (eds.) GD 2011. LNCS, vol. 7034, pp. 123–135. Springer, Heidelberg (2012)
6. Nguyen, Q., Eades, P., Hong, S.H.: On the faithfulness of graph visualizations. Tech. Rep. TR-690, University of Sydney (August 2012)
7. Van Wijk, J.: The value of visualization. In: IEEE VIS, pp. 79–86 (2005)