A Summary of Dynamic Networks Visualization Techniques

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Abstract

The visualization and analysis of dynamic networks have become increasingly important in several fields, such as social networks. Dynamic networks visualization deals with the problem of effectively presenting relationships as they change over time. The challenge in dynamic networks visualization is to compute a layout that is both revealing the structure of the entire network and fitting well into the sequence of drawings of the evolving network. In general, the dynamic visualization techniques combine the three main approaches mapping time with common used static network representations, such as node-link diagram, adjacency matrix, etc.

1. Introduction

Most of networks in real world are dynamically changing over time in nature, such as social networks, internet/telecommunications traffic, neural networks, financial analysis, among others. For example, in social networks, new members coming into the network or relationships changing cause network structures changing over time. The dynamic data sets tend to be complex due to more features added with time evolved and the tasks associated with them are often cognitively demanding. The dynamic and multi-relational nature of the data poses the challenge of understanding both its topological structure and how it changes over time [FAM*11].

The recent growth of of dynamic network analysis requires powerful visualization techniques to present and explore temporal network evolution. Designing visualizations of dynamic networks is challenging, but offers the ability to understand and explore the nature of networks. One of the main challenges in dynamic visualization is that of obtaining individually readable layouts for each moment in time, while at the same time preserving the viewer's mental map [HKV12]. The term mental map refers to the abstract structural information a user forms by looking at the layout of a graph [DG02]. In the context of dynamic graph drawing changes to this map should be minimal, in other words algorithms to draw sequences of graphs should preserve the mental map.

In general, to explore dynamic networks, three main approaches exist for representing time [MMBd05, BBD09, GEY12, BBD13, BPF14a]: animation which is a time-to-time mapping, timelines which encode time in 2D space, and space-time cube which encode time in 3D space.

Time-to-Time Mapping: A time-to-time mapping displays the network one step at a time, sometimes providing animations in-between.

Time-to-2DSpace Mapping: A time-to-space mapping shows the dynamic graph data as a static diagram and arranges subsequent graphs side-by-side on a timeline.

Time-to-3DSpace Mapping: A time-to-3Dspace mapping employ a three-dimensional visualization based on the space-time cube metaphor.

The remainder of the paper is organized as follows. Section 2 discusses the data model and characteristics of dynamic networks. In section 3, I introduce the visualization techniques based on time representation often used for visualizing dynamic networks. Section 4 presents the interview with a researcher working on dynamic graphs visualization. Finally, I conclude the report in section 5.

2. Dynamic Network Data

2.1. Data Model

To define a dynamic graph, we first introduce a static graph G = (V,E) that consists of a finite set of vertices (nodes) V and a finite set of edges (links or connections) E, between pairs (v,u) of V. Then, a dynamic graph is defined as a sequence of such static graphs. Edges in the graph can be modeled in different ways. If edges are directed, i.e. one node is the source, while the other is the target, the graph is called directed. Edges can have a weight associated with them. A graph with weighted edges is called a weighted graph. Further, a compound graph adds a hierarchical structure to the vertices, often used for interactively simplifying the graph by collapsing hierarchy vertices [BBDW14]. In a multivariate dynamic graph, edges/vertices have several attributes changing over time.

2.2. Graph/Network Characteristics

The goal of analyzing graph data is to retrieve characteristic properties of its structure and attributes [BBDW14]. The number of nodes in the graph indicates the graph size, while the number of edges is used to characterize graphs as sparse, dense, or fully-connected. Graph density is a visually important characteristic that poses numerous challenges to graph visualization [Bac14]. Centrality measures of network includes degree centrality calculated by the number of neighbors and betweenness centrality calculated by the number of shortest paths that a node is part of. The distribution of node degree is also an important measure to study the network. Beside the number or frequency of changes, another important property is dynamic variance showing the size of the change sets in relation to the size of the graph [BBD13].

In addition, another important feature is the community structure of networks that gives insight into the high-level organization of objects within the network [VBAW14]. In social networks, communities evolve as individuals change their roles, social status, or interests. An important goal of social network visualization therefore is to facilitate the discovery of communities and patterns that govern their evolution. The longest shortest path represents the diameter of a graph.

2.3. Graph/Network Category

Erten et al. [EHK*04] introduce three types of graphs that are often studied in dynamic networks visualization. The citation network for a given time period is a simple vertex-weighted directed graph in which the vertices correspond to distinct articles. A directed edge connects two articles, with the article that cites as the source and the cited article as the target. The weight of a vertex is determined by the number of citations an article received, divided by the number of years since its publication. The topic network for a given time period is a simple vertex-weighted and edge-weighted undirected graph in which vertices correspond to title words and edges are placed between title words that co-occur in research papers. The weight of a vertex in the topic graph is proportional to the number of papers that contain the corresponding word in their titles. Similarly, the edge weight is proportional to the number of papers in which the two corresponding words co-occur in the title. Collaboration networks are simple undirected node-weighted and edge weighted graphs. Vertices represent unique authors and there is an edge between two vertices if the respective authors have collaborated on a research paper. The weight of a vertex is determined by the author's collaborativeness and productivity. The weight of an edge represents the strength of the collaborative ties between two authors. In addition, affiliation networks [BHP06] are represented as a bipartite graph in which the elements of one vertex set (the actors) are only connected to (affiliated with) the elements of the other vertex set (the events). It is assumed that the events are timestamped and that there is a set of descriptors specifying their nature.

3. Dynamic Networks Visualization Techniques

A network representation describes the general visual representation of nodes and edges and how connectivity is encoded visually. Some of visualization techniques have been used frequently, for example: Node-link diagram, adjacency matrix, list representation, circle/ring layout, etc [BBD09]. Among these techniques, node-link diagrams and adjacency matrices are the two most common representations. **Node-Link.** Each vertex of the graph is represented by a single visual element (node). Relations between vertices are displayed as lines connecting their visual representations (links). **Matrix.** A vertex is represented vertically by a column and horizontally by a row. The appearance of a cell of the matrix indicates the existence of a certain edge that connects the vertices represented by the row and column intersecting at this cell. Ghoniem et al. [GFC05] state the matrix-based visualization outperforms node-link diagrams when graphs are bigger than twenty vertices. Only path finding is consistently in favor of node-link diagrams throughout the evaluation.

While static network visualizations are often divided into node-link and matrix representations, Beck et al. [BBDW14] identify the representation of time as the major distinguishing feature for dynamic graph visualizations: either graphs are represented as animated diagrams or as static charts based on a timeline. Bech et al. [BBD13] provide visualization profiles for representatives of three fundamental approaches to dynamic graph visualization: animated node-link diagrams, timeline-based node-link diagrams, and timeline-based matrix representations. Three examples shown in Fig 2 are Foresighted Layout with Tolerance [DG02], Parallel Edge Splatting [BVB*11], and Pixel-Oriented Matrix [SWS10].

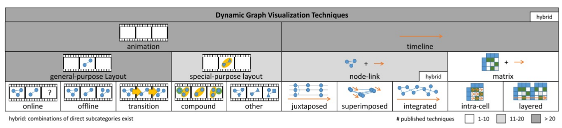


Figure 1: *Illustrated hierarchical taxonomy of dynamic graph visualization techniques [BBDW14].*

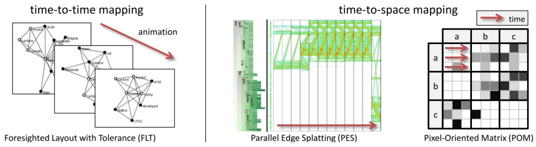


Figure 2: *Three representatives of dynamic graph visualization techniques [BBD13].*

3.1. Time-To-Time Mapping (Animation)

A mapping of the timestamps assigned to the sequence of graphs to visualization time results in an animated representation. Animating a series of dynamic graphs seems to have the advantage that the entire screen can be devoted to the drawing of the graph [APP11]. Beck et al. [BBDW14] indicate that almost all animated approaches are based on node-link diagrams. Hence, this category refers to node-link or node-link based approaches only. GraphAEL [EHK*04] supports the node-link based layout of graphs with node-weights and edge-weights, as well as the notion of a timeslice which is used to visualize evolving graphs with a temporal component. Frishman and Tal present a method for drawing a sequence of graphs online based on force-directed node-link layout [FT08], and also develop an algorithm for drawing a sequence of graphs (Fig 3) that contain an inherent grouping of their vertex set into clusters [FT04]. The algorithm computes a compact and space efficient graph layout, while minimizing the displacement and changes to clusters between layout iterations. There are some studies about the impact of different dynamic graph metrics on user perception of the animation. Ghani et al. [GEY12] perform an in-depth quantitative evaluation of dynamic graph perception using animated node-link diagrams. They find significant effects of node movement and target separation on user performance, which are consistent with existing work in the literature. Unlike the traditional node-link diagram, Turker and Balcisoy [TB14] propose a Hyperbolic Temporal Layout Method (HTLM) which draws the layout in the Hyperbolic space and project this Hyperbolic space in an Euclidean sphere. It derives prominences of nodes from user selected network metrics, then uses these values to calculate nodes' sizes and position prominent nodes close to the centre of the Hyperbolic space and others on circular orbits. Fig 4 displays a sample output of their method.

Animating a node-link diagram also requires the transitions between timeslices that may help users understand how the graph structure evolves [APP11]. Back et al. [BPF14a] design a visual interface-GraphDiaries to improve support for identifying, tracking and understanding changes in dynamic networks. It relies on animated transitions that highlight changes in the network between time steps, thus helping users identify and understand those changes. Fig 5 shows staged transitions with change highlighting.

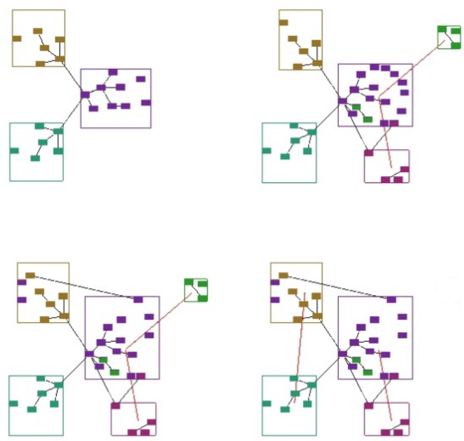


Figure 3: *Snapshots from an animation sequence [FT04].*

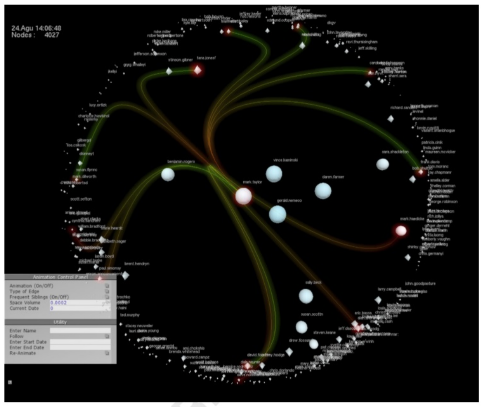


Figure 4: *Visual representation of a temporal dataset with 4027 nodes and 12 edges [TB14].*

3.2. Time-To-2DSpace Mapping (Timeline)

Animation can be used to visualize the dynamic changes in networks. However, the exploration of animated graph diagrams leads to high cognitive efforts due to our limited short term memory [BVB*11]. A better overview is provided if the time dimension is mapped onto a timeline and the dynamic graph is visualized in a single static image [BBW12]. Compared to animation, timeline approach is easier for users to identify changes in the context of the evolution as they are still visualized on the screen. In timeline-based representations for time, three approaches are mainly used for temporal data visualization: line graph, node-link layout, and radial-based layout.

3.2.1. Line Graph

Two papers about dynamic communities visualization are found to use line graphs to represent individual vertex

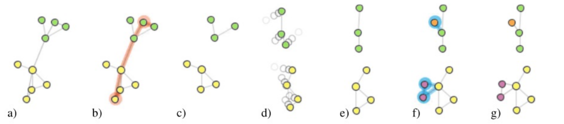


Figure 5: *a) initial state, b) element removal (red halos), c) remaining elements only, d) layout adaption, e) remaining elements at their new position, f) element addition (blue halos), and g) final state [BPF14a].*

with color-coded presenting community identity. Reda et al. [RTJ*11] focus on revealing the community structure implied by the evolving interaction patterns between individuals in dynamic social networks. They use a layout similar to a timeline chart depicting a time series. The X axis is used to represent time, while the Y axis is used to position individuals in their appropriate communities. This allows users to use the vertical space in the chart to group individuals rather than drawing edges between them. Fig 6 shows an example of the visualization. Red threads represent Republicans while the blue threads represent Democratic representatives. However, only visualizing dynamic community structure cannot satisfy some certain tasks. Hence, Vehlow et al. [VBAW14] develop a visualization approach that combines a dynamic community structure with a dynamic graph in a single image and helps reveal typical life time phenomena of communities. In both of these two visualizations, the representations of communities as spatially divided blocks help identify communities and the explicit visualization of transitions helps identify changes in the community structure.

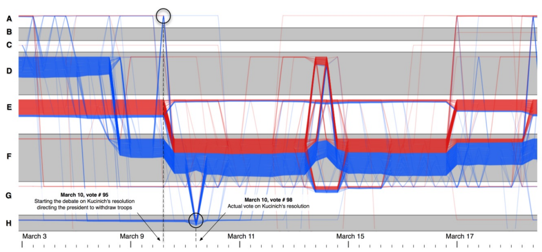


Figure 6: *Portion of US House of Representatives roll call votes covering the period of March 3 through 18, 2010 [RTJ*11].*

3.2.2. Node-Link Layout

Placing node-link diagrams on a timeline is simple. Node-link diagrams just need to be positioned next to each other, preferably applying a fixed layout of the nodes [BBDW14]. TimeArcTrees [GBD09] is a visualization of weighted, dynamic compound digraphs by drawing a sequence of node-link diagrams in a single view (Fig 8). The graph nodes are vertically aligned and edges are visualized as colored

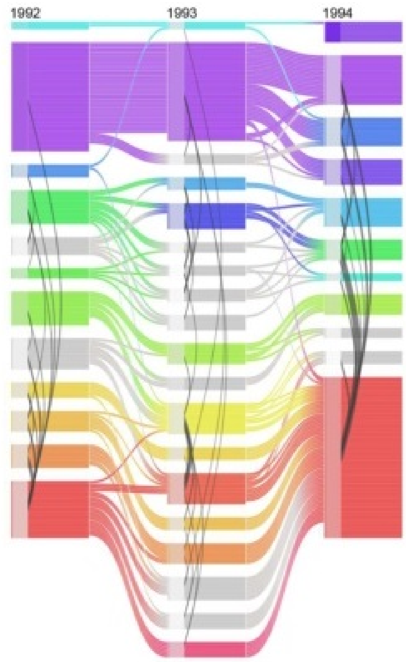


Figure 7: *Three time steps of the soccer data example [VBAW14].*

arcs. The more reddish the color of the edge, the higher is its weight. Horizontal alignment of the instances of the same node in different graphs facilitates comparison of the graphs in the sequence. Based on node-link diagrams, Burch et al. [BVB*11] present a dynamic graph visualization technique that draws the graphs side-by-side from left to right as a sequence of narrow stripes that are placed perpendicular to the horizontal time line. The vertices are arranged along the vertical borders of these stripes, according to the order implied by the hierarchy. Directed edges connecting these vertices are drawn from left to right with a splatting technique applied to tackle overlapping edges (Fig 9).

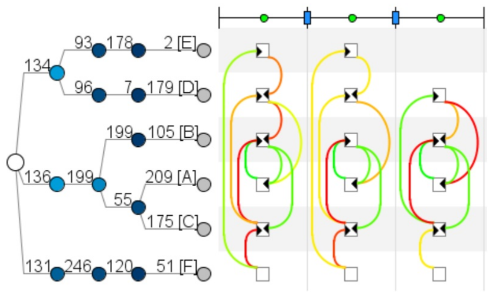


Figure 8: *The TimeArcTrees visualization for a sequence of three graphs [GBD09].*

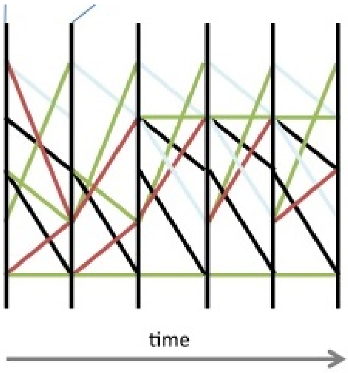


Figure 9: *A sequence of five directed and weighted graphs represented as a layered icicle plot [BVB*11].*

3.2.3. Radial-Based Layout

In the radial-based layout, the exploration of time-varying relational data is facilitated by aligning graph patterns radially. The temporal evolution of the graph is mapped to rings that grow outward from the center of the circle. The radial layout emphasizes newer graphs, displayed in the larger, outer parts of the circle. The strength of this visualization technique lies in the visual encoding of time-series relational data in a single view without animation, which helps to preserve the mental map and hence to reduce cognitive efforts [BFBD10].

Brandes et al. [BHP06] use a radial ripple metaphor to display the passing of time and conveys relations among the different constituents through appropriate layout. Fig 10 shows an example of the radial layout. Most recent events are placed prominently in the center while older events are placed more peripherically. Fixed positions for the descriptors are chosen on a descriptor circle that borders the layout to set up a conceptual context for the events. The time interval under consideration is divided into discrete fine-grained ticks, and for each tick a time ripple is introduced. As time progesses, the ripple grows larger in radius, but stays centered in the middle of the drawing. An event appearing in the layout remains fixed to the time ripple corresponding to its time stamp.

Burch and Diehl [BD08] present a TimeRadarTree approach to visualize sequences of compound weighted digraphs. It uses radial tree layout to draw the hierarchy, and circle sectors to represent the temporal change of edges in the digraphs. TimeRadarTree (Fig 11) approach integrates three views into one: **Interactive radial tree** shows the whole hierarchy to an interactively selectable level. **Inner Circle** displays incoming edges of leaf nodes or collapsed subtrees as colored parts of a circle sector related to that node or subtree. The smaller **Outer Circles** related with each hierarchy node show the outgoing edges of the related node.

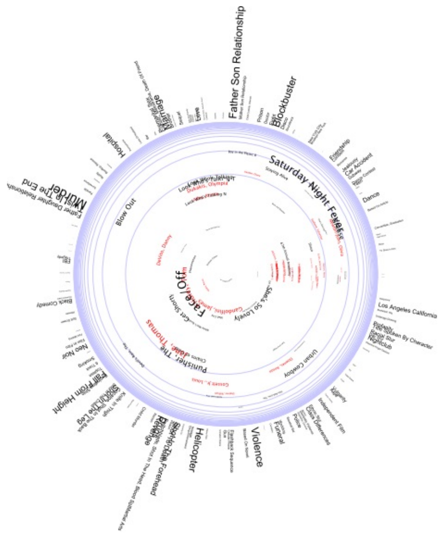


Figure 10: *A snspshot of John TravoltaâĂŹs movie biography layout in 1999 [BHP06]. Dancing and music movies are concentrated in the upper right region, while his later movies tend downwards.*

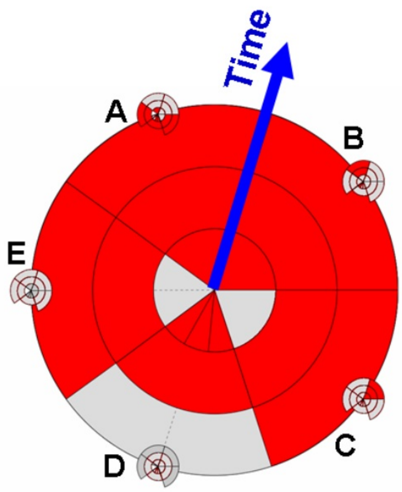


Figure 11: *TimeRadarTree of a sequence of graphs [BD08].*

Burch et al. [BHW11] then combine Indented Tree Plots and TimeRadarTrees to show the temporal evolution of relations in a static view (Fig 12). The graph edges are layered around thumbnail wheels consisting of color-coded sectors that are representatives of the graph nodes. These sectors generate implicit representations of graph edges. TimeSpiderTrees [BFBD10] is also based on a radial node-link layout. Relations are visually indicated by orientation instead of connectedness to circumvent the problem of edge crossings. Burch et al. [BBW12] exploit the node-link visual metaphor [BVB*11] and use radial layout encoding dynamic directed graphs on narrow rings of a circle (Fig 13). Graph vertices are placed equidistantly at the borderlines of each ring and edges as curved lines inside the narrow annuli (circle rings) pointing from an inner to an outer annulus. In addition, their edge layout algorithm minimizes link length by picking the shorter of the two potential links (clockwise and counter clockwise). Vehlow et al. [VBSW13] propose a radial layered matrix visualization in which the vertices can also be hierarchically organized. Techniques like arranging the nodes onto circle rings and applying edge splatting are used to increase the scalability of the single graph diagrams.

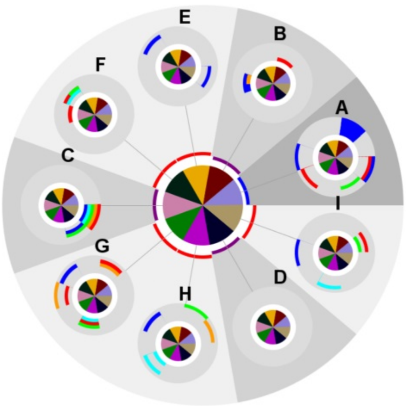


Figure 12: *Directed relations of the dynamic graphs are visually encoded as color-coded sectors and put on top of each representative ThumbWheel at the corresponding circle sectors [BHW11].*

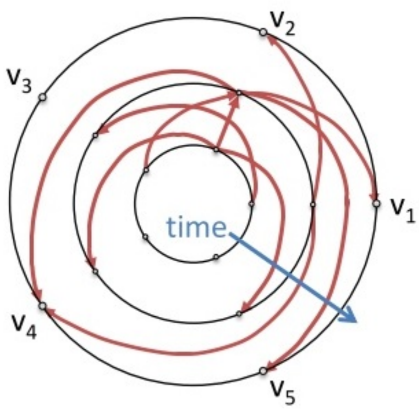
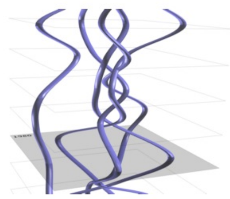


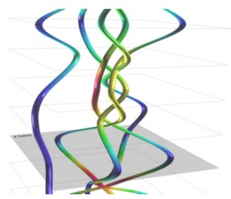
Figure 13: *A sequence of two directed graphs starting in the circle center and ending with the newest graph at the outside [BBW12] .*

3.3. Time-To-3DSpace Mapping (Space-Time Cube)

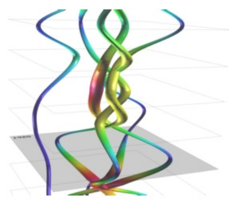
The term space-time cube originates from cartography, where it refers to a geographical representation where time is treated as a third dimension [BDA*14]. Although Space-Time Cubes have not been widely used as a conceptual model for reflecting on temporal visualization techniques yet, it is worth exploring this representation for visualizing dynamic data since the two studies below prove the power part of the space-time cube representation. Recently, it has started to be considered as a technique for visualizing temporal data. Groh et al. [GHW09] visualizes streaming event data of social interactions by an interactive three-dimensional model of interpolated NURBS (Non Uniform Rational B-Splines) "tubes" (Fig 14), representing activity and social proximity within a given set of actors during a given time period. Three attributes can be visualized in our "tube-only" model via tube-distance, tube-color and tube-diameter. The Matrix Cube [BPF14b] is a representation of dynamic networks based on the space-time cube metaphor. It is created by stacking adjacency matrices in chronological order, one for each time step. Fig 15 shows an example. Red edges of the cube hold nodes and correspond to the rows and columns of the constituent adjacency matrices; blue edges of the cube hold time steps. Users can change their perspective on the data by rotating or decomposing the 3D cube. These manipulations can produce a range of different 2D visualizations (Fig 16 (b)) that emphasize specific aspects of the dynamic network suited to particular analysis tasks.



(a) Tube-only display



(b) Color mapping

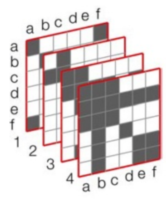


(c) Color and radius mapping

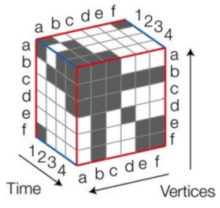
Figure 14: *Tube-only model without and with mapping of degree centrality onto temporal axis [GHW09].*

3.4. Hybrid

While most dynamic graph visualization techniques can be classified as either using time-to-time mapping or time-to-space mapping, a few approaches combine both mappings of time. The combination of the two time representations



(a) Adjacency Matrices



(b) Matrix Cube

Figure 15: *The Matrix Cube. (a) Each time step of the network (1,2,3,4), is represented as an adjacency matrix. (b) The Matrix Cube results from stacking those matrices [BPF14b].*

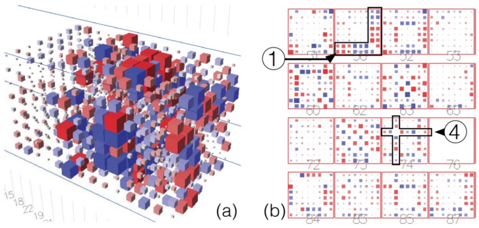


Figure 16: *Brain connectivity data. 8 regions over a sample of 15 time steps. (a) Overview reveals that some time steps are more active than others. (b) Detailed view of 16 time slices [BPF14b].*

can follow different strategies in those hybrid approaches. Gaertler and Wagenr [GW06] describe a hybrid model for dynamic graph drawing that allows a simultaneous representation of both, a cumulative and an animated view. Both views are integrated in such a way that the hybrid layout reveals each of them by changing the perspective or adjusting visual effects, like color or transparency. Federico et al. [FAM*11] propose a visual analytics approach for analyzing dynamic networks consisting of those three temporal views based on different combinations of node-link diagrams; network analysis metrics; and specific interaction techniques.

4. Interview

Below is the interview with Fabian Beck who is researcher at VISUS, University of Stuttgart. He has been working on dynamic data visualization.

Q: What is the main research project you work on?

A: I'd rather name two: i) Scalable visualization of dynamic graphs; and ii) Augment source code, user interfaces, and text with word-sized visualizations.

Q: What would be an ideal result from your research?

A: I don't believe that there is something like an ideal result', all insights are valuable.

Q: What kind of data do you work with most often in your research?

A: Graphs and hierarchies, often representing dependencies and modularizations in software systems. By studying software evolution or program executions, these data structures become dynamic.

Q: How do you gather or generate this data?

A: Mining software repositories and recording program executions.

Q: How is this data used/analyzed?

A: Custom visualizations, standard clustering techniques.

Q: What visualization tools/techniques do you use to help make sense of this data?

A: Custom visualizations often consisting of node-link diagrams, adjacency matrices, timelines, icicle plots, and sparklines.

Q: What visualization tools/techniques do you use to display the data and/or communicate with other experts in your field?

A: See above. However, often I don't communicate with others about data, but about ideas for new visualization techniques. I use mockups a lot, sketched by hand or prototyped in PowerPoint.

I also interviewed Benjamin Bach who is currently a postdoctoral research fellow investigating and creating interactive visualizations for network data. His post-doc research focuses on the visualization of functional brain connectivity.

Q: Why is there little research on dynamic matrix-based representations for dynamic networks visualization? Matrix Cubes may be a starting point, but how about animated matrices?

A: There is some work but I guess node-link diagrams are still more intuitive to people, both in terms of representation (nodes and links) as well as in terms of time. The problem with matrices is that they don't change as much. You can change the reordering (e.g. using animated transition) but changes in that linear ordering preserve less well the mental map. While matrices are already hard to read by many people (especially in the large public, and when you communicate to many infovis-lay people), understanding how they convey temporal changes is even harder. Note that these are guesses and I have no evidence for that. I continue research with matrices and try to highlight cases where there are superior to node-link diagrams for dynamic networks, because they are geometrically simpler (e.g. the Matrix Cube). Perhaps its the matrices' geometric simplicity that is of potential (besides that they don't clutter with many connections).

Q: I know you are working on brain connectivity visualization. Brain networks have physical spatial structures. Do you have any thoughts on visualizing such networks with both temporal and spatial embedded? I just feel there would be a lot of tasks to analyze brain networks, such as finding the relationship between spatial structures and functional connections, the evolution of the entire network/clusters in the networks, behavior of individual node over time, etc.

A: That is a very good question. I am not directly working on 3D representations but had recent discussions about. I am curious to see some work there, especially novel creative designs. I have no good idea yet. While 3D is already hard on 2D screens, time adds more complexity. Perhaps we can learn something from the space time cube, but I am not sure yet. There has been work in the scientific community about storms and blood flows. Perhaps that can give us a hint. Interestingly, 3D networks don't seem considered as an infovis problem (because they're 3D) and already 2D geographic networks are not yet solved.

5. Discussion and Conclusions

This report presented the state of the art in visualizing dynamical networks. Dynamic graphs are often represented as an animated sequence of graphs or shown as a sequence of single images put next to each other as in one single image. Both of time representations have advantages and disadvantages. Animation has the advantage to draw the graph on the entire screen and help users understand how the graph structure evolves with transitions. However, it can increase users' cognitive load by forcing them to remember the network's state when navigating between time steps. Timeline-based representation provides a quick overview of the network's evolution but make it hard to track individual graph elements across steps, or directly compare distant images, especially for dense graphs. Although Space-Time Cubes have not been widely used as temporal visualization techniques yet, a few studies have shown the value in visualizing dynamic networks.

In the report, I only present three types of layouts of network visualizations. Hence, there is still a large room to design new visualization techniques with different combinations of network representations and time representations. In addition, an important problem that is not discussed in the report is there is a need for finding good matching between dynamic data/tasks and visualization applications.

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