A Visual Analytics Approach to Dynamic Social Networks

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ABSTRACT
The visualization and analysis of dynamic networks have become increasingly important in several fields, for instance sociology or economics. The dynamic and multi-relational nature of this data poses the challenge of understanding both its topological structure and how it changes over time. In this paper we propose a visual analytics approach for analyzing dynamic networks that integrates: a dynamic layout with user-controlled trade-off between stability and consistency; three temporal views based on different combinations of node-link diagrams (layer superimposition, layer juxtaposition, and two-and-a-half-dimensional view); the visualization of social network analysis metrics; and specific interaction techniques for tracking node trajectories and node connectivity over time. This integration of visual, interactive, and automatic methods supports the multi-faceted analysis of dynamically changing networks.

Categories and Subject Descriptors
H.5.m **[Information Systems]**: Information Interfaces And Presentation (e.g., HCI) – *Miscellaneous* , I.3.6 **[Computing Methodologies]**: Computer Graphics – *Methodology and Techniques*, J.5 **[Computer Applications]**: Social and Behavioral Sciences.

General Terms
Design.

Keywords
Dynamic layout, dynamic networks, graph drawing, interaction, social network analysis, information visualization, visual analytics.

1. INTRODUCTION
Dynamic social networks are social networks that take into account changes over time [10]. They not only model relations between human beings in terms of interpersonal interactions, but also consider the evolution of these relations, i.e. the way and the extent by which they change over time. Dynamic social networks can be useful to model and analyze human relationships in several potential scenarios: the informal social relationships of individuals within a family or a group of friends; the structured collaboration of employees in a large enterprise; the widespread connections through social networking services; or the covert activities of small, interconnected terrorist cells.

On the one hand, dynamic networks are capable of modeling such diverse problems, but on the other hand, they are complex in many respects and they are not easy to grasp for non-expert users. For this reason we designed and developed a research prototype aiming to facilitate the interactive exploration of dynamic networks, the comprehension of their structure and in particular how these structures change over time. We adopted a visual analytics approach by combining interactive visualization techniques with automated analysis methods, taking into account some basic perceptual aspects. The main features of our proposed solution are:

- A dynamic interactive layout, whose balance between stability and consistency can be controlled by the users, in order to adapt it to the tasks s/he wants to complete and the data s/he needs to examine.
- Three alternative views for visualizing network dynamics, and animated smooth transitions between them.
- The integration of automatically computed Social Network Analysis (SNA) metrics into the interactive visualization.
- The visualization of node trajectories by which users can focus on specific nodes and track their evolution.
- A specific interaction technique to highlight particular nodes and their neighbors.

In section 2, we discuss related work. Then we describe the problem we considered and provide some details about users and tasks in section 3. In section 4 we illustrate our design and explain the choices we made. Finally, we outline our future plans for improving and substantiating this work in section 5.

2. RELATED WORK
Since the first *sociogram* was introduced in 1934 [36], several methods have been proposed for visualizing static social networks [20]. Recently, the interactive visualization of dynamic networks and its integration with analytical methods has become an emerging research field.

2.1 Static networks
If we disregard at first the dynamics and consider the problem of visualizing static networks only, we find several visualization techniques proposed in Graph Drawing [14], Information

Visualization [28], and Data Mining [13] communities. While the usual way to draw a network on a two-dimensional surface is a node-link diagram, we may also draw a network using a matrix-based representation [25]. While node-link diagrams do not scale well for large graphs, matrix-based representations make it harder to find a path between two nodes. Besides the choice of a model for the visual representation, a layout model is needed. Pure network data, indeed, do not provide any a priori criterion to determine the geometric properties for a representation. For matrix-based representations, for example, the reorderable-matrix layout is computed by permuting rows and columns in order to block similar nodes [4]. With reference to node-link diagrams, several proposed criteria could drive the optimization of the graph layout in order to enhance its perception. Examples for such criteria that are also referred to as aesthetics are [12]: minimizing edge crossings, preserving symmetry, minimizing edge bends, minimizing edge lengths. Since absolute position is a prominent visual variable, a 'good layout' not only has to enhance perception, but also has to maximize the conveyed information. For instance, spring-embedder algorithms use a physical metaphor that models nodes as repulsing particles and edges as elastic springs [24, 29].

2.2 Dynamic networks

The paradigm shift from structures to dynamics, i.e., the trend to shift from the structure-centric paradigm to the visualization of dynamic properties of underlying phenomena, has been described as one of the top unsolved information visualization problems [11]. Once we have explored different possibilities for the network representation and for the layout, it is worth to notice that the issue of visualizing network dynamics is not solved by obtaining a temporal sequence of static images. We need to obtain a sequence of dynamic layouts that facilitates the perception of changes by taking into account additional criteria, such as ensuring repeatability, comparability and stability [3]; preserving orthogonality, proximity and topology [8]; preserving planarity [19]; preserving edge directions [5]; preserving position and distances [9]; and restricting adjustments to small parts [34]. In a general sense, a good dynamic layout must preserve the user's mental map [17]; it must minimize unnecessary changes while emphasizing temporal trends or patterns. This causes a conflict between two opposite needs: on the one hand, each layout in the sequence must comply with the aesthetics criteria and must be consistent with the metaphor on which it is based and with its meaning; on the other hand, all layouts must preserve the user's mental map. The aforementioned criteria have led to the development of several dynamic layout techniques, which we can group mainly to two families: offline and online algorithms. Offline algorithms need the entire sequence of temporal graphs, which are then aggregated into a compound graph, i.e., an overall or 'foresighted' layout is computed as a base for obtaining stable layouts [15, 30]. Online algorithms can compute a dynamic layout in an incremental fashion, by taking into account only previous time slices [23, 31]. Moody et al. [35] provide a common conceptual framework for both approaches: binding nodes to anchors ensures the dynamic stability. Anchors can be put on random or fixed positions as well as based on the positions of the nodes in the aggregated layout or the positions of the nodes in the previous time slice. Anchors can also consist in the position of other instances of the same node in the other time slices [18].

Scholars have proposed different analytical methods to automatically set the balance between stability and consistency [37], or between stability and local quality [7]. Empirical studies, nevertheless, have shown that the preservation of the mental map is not important in every circumstance [41] and that the extent of this preservation (or, conversely, the extent of the allowed difference between graph layouts in the sequence) depends on the data and the task [40], and presumably on the user, too.

Given the sequence of dynamic layouts obtained by any of the aforementioned algorithms, we can rely on different proposed approaches to visualize them: animation (obtained as a simple flip-book-like series of dynamically laid out node-link diagrams or morphed through smooth interpolations [5, 22, 32]); superimposition (in which diagrams overlay one another [6]); juxtaposition (side-by-side displacement [1]); two-and-a-half-dimensional view (where two-dimensional diagrams are arranged in a stacked pile [16, 18, 26]).

2.3 Analytics

Analytical methods usually employed for social network analysis are based on models, metrics, and algorithms of Graph Theory [45]. Examples for common metrics are different kinds of node centralities that determine the relative importance of a given node on the base of its connection to other nodes. Popular algorithms are those for finding communities, i.e., node clusters with dense connections within them and sparse connections between them. The integration of analytical methods into an interactive visualization can support the comprehension of relational and temporal aspects of dynamic networks. A common approach is to compute some static SNA metrics associated to nodes and edges and mapping them to any visual variable (see for example [39], where information visualization and statistical methods are combined, and [46], where event-driven information for characterizing temporal evolution is used). Perer and Shneiderman [38] and Tomiski et al. [43] also exploit these metrics to perform dynamic filtering and some form of multidimensional data reduction, also combining visualization and exploratory data analysis techniques. Besides metrics associated to nodes and edges, analytical methods can compute overall metrics and thus provide synthetic descriptions of the entire network at given instants or intervals. Such synthetic descriptions can enable a coarse-grained visual comparison of a large number of networks [21].

3. PROBLEM DESCRIPTION

Time is only one of several aspects of the complexity of dynamic (social) networks. Such networks are of course temporal but in general they can also be large, multipex, multi-modal, and probabilistic [10]. They are large because they have a large number of nodes and edges and a complex topology. They are multiplex, because more than one edge is allowed for each pair of vertices, and also multi-relational, if these edges are of different types. They are multimodal, since there can be also different types of nodes and they are probabilistic, since a probability is associated to the occurrence of edges and to their attributes. In our contribution we particularly refer to organizational networks, i.e., networks within an organization, like for example an enterprise. Moreover, we disregard the multi-modality, considering only employees as nodes and leaving out roles, skills, tasks, and any other organizational data. We also disregard probabilistic aspects but we consider multiple types of relations (e.g. communication, collaboration, reporting). As for size, we limit ourselves to companies with up to one hundred employees. Network data are collected on a regular basis via questionnaires. Hence, our time domain is not continuous, but consisting of a sequence of time slices.

Having defined the scope and the features of the data, we conducted preliminary interviews with potential users to outline their needs and a list of requested features. We chose subjects to interview from two groups: network analysis experts and business users with managing function (i.e., non-experts with respect to network analysis). We questioned 11 persons using a semi-structured interview method. The questions consisted of potential application scenarios (e.g., what managers need to know about networks), data handling (e.g., online questionnaires), network measurements (e.g., static and dynamic methods) and visualization techniques (e.g., graph drawing). The interviews lasted between one and two hours each. Then we analyzed the audio recordings with a qualitative method [42]. Based on this, we identified the most important tasks and functionalities, and elicited a list of both simple and complex tasks. A simple task, for example, is the monitoring of a network indicator for a certain person over time; a complex task could be a before/after comparison of the entire network to evaluate management intervention. Given a rough sketch of data, users, and tasks, we engaged in the design of our visual analytics prototype.

4. DESIGN CHOICES

The first choice when dealing with the visualization of networks concerns the basic mapping of entities and relationships to a certain representation. In our case we chose a node-link diagram because they are the most popular kind of visualization for dynamic networks and consequently they require a shorter learning period to be effectively used than other forms of representation. We also considered matrix-based visualizations, which are popular in different contexts and might also be easy to understand, but they are not as efficient for visualizing paths and, most of all, multiplex and multi-relational networks that are the focus of our research.

4.1 Dynamic layout

Once we have chosen a specific visualization, the next step is the graph layout. The layout is a very important part of the design of the network visualizations, since 'position' is one of the most prominent visual variables. We aimed for a layout that enhances the perception of both, the relational aspects (the network structure) and the temporal aspects (the network evolution). Here we find the well-know conundrum already introduced in section 2: stability versus consistency. An additional requirement was the high interactivity of the visualization, like for example the direct manipulation of the networks, which involves the possibility for the user to drag-and-drop single nodes while the layout automatically reacts to these changes and adjusts accordingly. Moreover, we assume that a simple physical metaphor would further enhance the comprehension for non-expert users while algorithms based on more formal mathematical concepts would require longer learning periods.

According to this last consideration we decided to adopt a force-directed algorithm using the spring-embedder metaphor: nodes are modeled as repulsing particles while edges are modeled as elastic springs. This physical model roughly ensures that nodes with more connections tend to occupy a more central position, while nodes with fewer connections are pushed towards the periphery. Moreover, it clusters connected nodes and, finally, it can deal with multi-relational networks treating different types of relations as edges with different weights. Then, we adopted an incremental and continuously running algorithm for the layout that allows the users to directly manipulate the diagram and also enables more sophisticated interaction techniques. Next, we tackled the issue of choosing a good layout to deal with the topology and the evolution in an appropriate manner, i.e., a manner that enhances their perception. Since the ideal balance between stability and consistency seems to be dependent on the task and on the data, tuning this trade-off by automatic methods could result in counter-intuitive representations. For this reason we provided the user with the possibility to interactively control this balance. In order to do so, we adopted an anchoring mechanism and made the anchors dynamic. We discarded the use of predetermined positions (they would not allow for free direct manipulation), then we discarded anchors consisting of the positions of nodes in the aggregated graph (which ensure stability but not consistency) and also discarded anchors consisting of the positions of nodes in the previous time slice (because our layout must be computed all at once in order to enable full interactivity). Finally, we adopted a dynamic anchoring mechanism, similar to the one used in GraphAEL [18], but we used a continuously running layout algorithm with a user-controllable trade-off between stability and consistency. All the instances of that node in precedent and subsequent time slices are considered as anchors for that node, and the positions of all instances are computed simultaneously. Particularly, we introduced new edges (red lines in Figure 1) that link different instances of the same node in different time slices in a chain fashion. The length and the force constant of these new edges, which compose the chain, are interactively controlled by the user. The parameters of existing edges that connect different nodes in the same time slices do not vary. A simple slider in the GUI allows the user to select seamlessly between stability and consistency. When the user moves the slider towards consistency, the force constant of the chain decreases and its length increases. Hence, the different instances of the same node become almost independent and their positions are computed according only to other nodes and edges in the same time slice (Fig 1.d). Conversely, when s/he moves the slider towards stability, the force constant of the chain increases and its length decreases. Thus, the different instances of the same node end up at approximately the same position (Fig 1.e)

In Figure 2 we show an example of a social network over two time slices. When the balance of the dynamic layout is set to maximum stability (Fig. 2.a), nodes hold approximately their position and it is easier to locate a certain person and track social

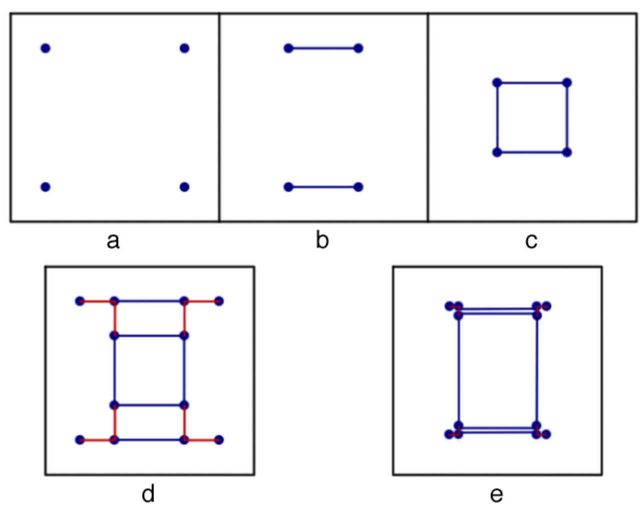

Figure 1. Dynamic chain model for a network with three time slices: (a, b, c) independently computed static layouts; (d) dynamic layout computed with maximum consistency; (e) dynamic layout computed with maximum stability.

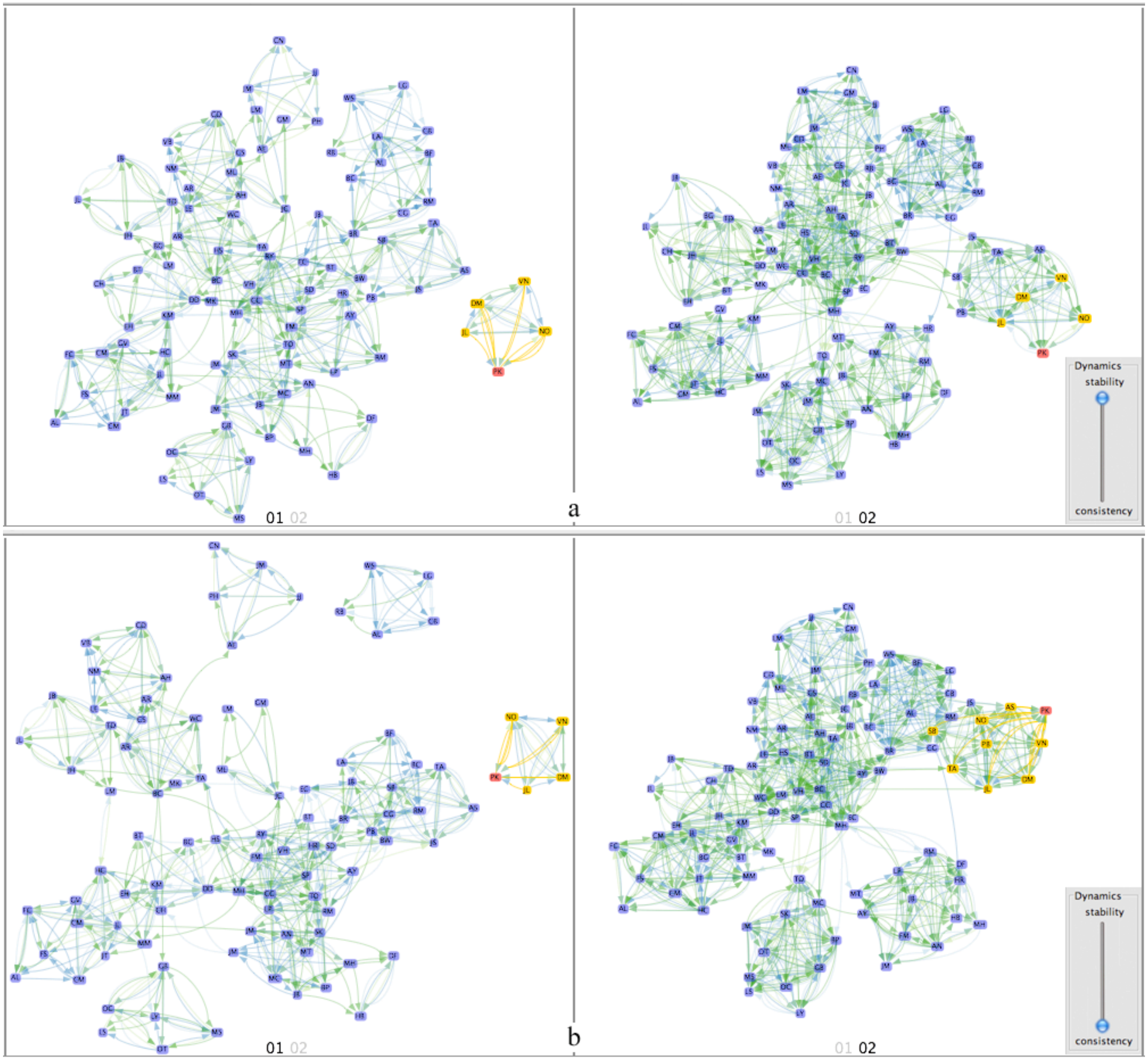

Figure 2. Two juxtaposition views of a network, each view showing two time slices. The balance of the dynamic layout is set to maximum stability in (a), enabling the detailed tracking of single nodes since they approximately hold their positions, and to maximum consistency in (b), enabling the perception of an overall insight (small clusters merge into bigger ones). The node highlighting (discussed in section 4.5) is performed in edges-first mode in (a) and in trajectories-first mode in (b).

relationships over time slices. Setting the balance to maximum consistency (Fig. 2.b) enables the perception of an overall insight, for example the fact that small groups of five to six persons merge into bigger ones. We think that this integration of graph drawing algorithms with interaction techniques, driven by perceptual principles, can support the visual analysis of dynamic networks.

In our prototypical implementation we used a force-directed layout based on the Barnes-Hut algorithm [2]. In order to implement our dynamic chain mechanism, we added the inter-time edges, whose spring forces and lengths are user-controlled, and reduced repulsing forces between nodes in different time slices. The setting of parameters, namely the residual repulsing force between nodes in different time slices as well as the length and the elastic coefficient of inter-time edges, is tricky. We want some residual force to avoid node overlapping. But if this force is too strong with respect to the elastic force of inter-time edges the node instances create large clusters according to their time slice only and the results fail to meet the objective of our dynamic chain layout concept. As for computational complexity, the additional edges do not overly affect the occupation of memory and the speed of computation, since they are n for each time slice (n being the number of nodes), while normal edges are n^2 for each time slice in the worst case.

4.2 Views

In the previous section we introduced a technique for improving the layout of dynamic networks. In this section we discuss how adequate visualizations can support their exploration and in particular how the temporal dimension can be visually encoded. Mapping time to time (i.e., animation) is a popular approach, and there is evidence that it enhances the perception of change [33]. In contrast to that, some of the experts we interviewed pointed out that animation might interfere with a detailed exploration and might also hamper the comparison between different time slices, which can be performed only in the user's memory. Focusing on changes over time, we decided to explore alternative views and their combination.

4.2.1 *Juxtaposition view*

By placing node-link diagrams of different time slices side by side, we obtain a juxtaposition view (Fig. 2.a and b) that we may understand as a mapping of time to space (the horizontal axis, in our case). This view applies the principle of small multiples [44] and allows the reader to compare the time slices and find commonalities and differences. Visual analysis is further

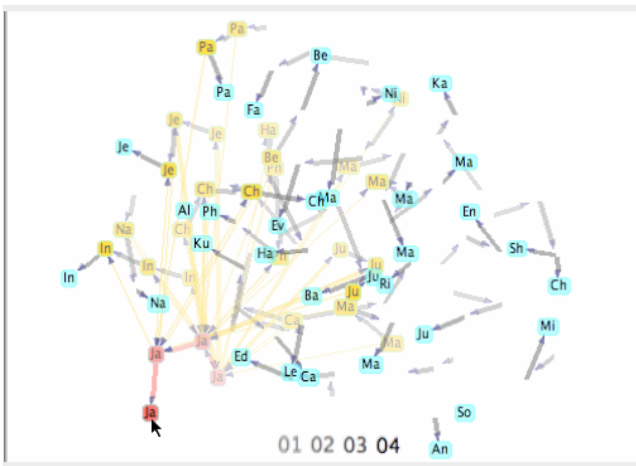

Figure 3. A superimposition view of four time slices. Trajectories of all nodes are visualized as gray directed polygonal chains. The node "Ja" under the mouse cursor is highlighted in red, while its neighbors are highlighted in yellow. The most recent instances are opaque, previous ones are increasingly transparent. "Ja" has been loosing connections, so it moves from the center to the periphery.

facilitated by linking the different frames by interaction features like coordinated zooming & panning and coordinated highlighting, which make exploration and comparison easier. The drawback of juxtaposition is that it takes up more display space: the more time slices we want to visualize, the more display space is needed.

4.2.2 *Superimposition view*

With respect to screen occupancy, we can attain a better performance by superimposing the diagrams (Fig. 3). In this case, a visual variable must be employed to differentiate between time slices (hence we can refer to superimposition as a mapping of time to visual variable). We used transparency, so that more recent elements are more opaque. Besides the fact that less screen space is used, this has the advantage of reducing the eye movement from one slice to the other compared to juxtaposition and preserves the context. The main disadvantage of this view is the concentration of all edges and nodes within the same diagram with a large number of edge crossings and occlusions that impair readability. In order to reduce visual clutter, we allow users to interactively select the elements (trajectories, nodes or edges) to be shown persistently or by hovering.

4.2.3 *Two-and-a-half-dimensional view*

Mapping time to an additional spatial dimension results in a two-and-a-half-dimensional view (Fig. 4). In such a view, we draw diagrams for each time slice on separate transparent planes, stacked along the horizontal time axis. It combines some of the advantages of the two aforementioned views. Moreover, the added spatial dimension offers us the opportunity to include additional information within this view, as we will describe in section 4.4. The disadvantage is that diagrams are distorted and occlusion may occur between planes. We let the user find the best viewpoint to reduce this occlusion, providing her/him with 3D zooming, rotating, and panning controls.

4.2.4 *Combination of the three views*

Each of the three views introduced in the previous sections has advantages and disadvantages and might be efficient for certain data or a particular task. Hence, we exploited them all, and integrated them into our prototype. Moreover, exploring a complex network, the user might happen to switch repeatedly between views. Therefore, we wanted to preserve the user's mental map (in a broader sense than the one we have discussed in

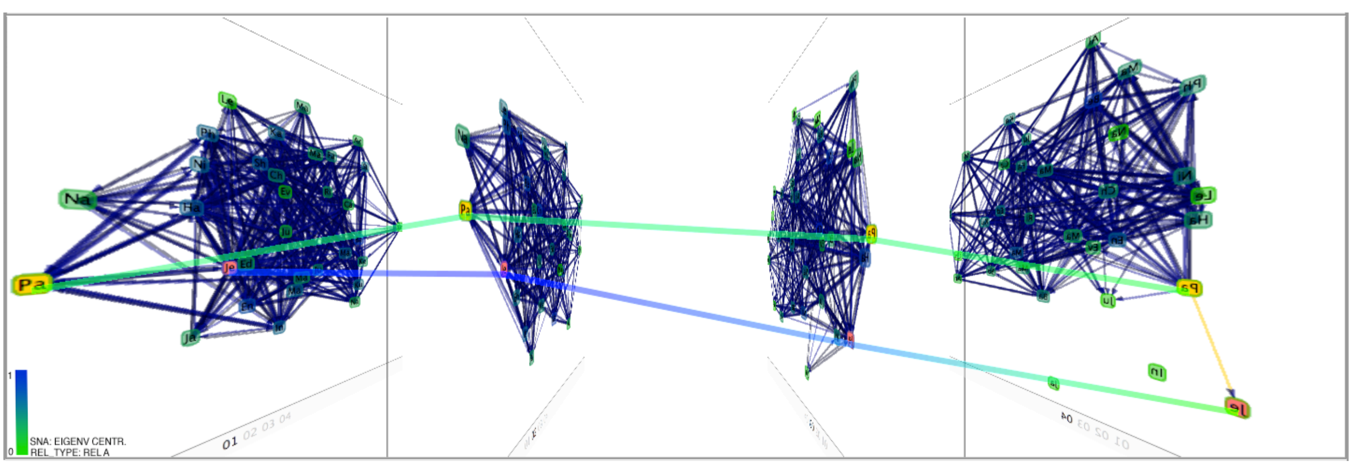

Figure 4. A two-and-a-half-dimensional view of four time slices. Trajectories of selected nodes are visualized as polygonal chains. An SNA centrality metric is mapped to the color of nodes and trajectories, enabling the tracking of their evolution: values are about constant for "Pa" (green trajectory) while they are decreasing for "Je" (blue-green trajectory).

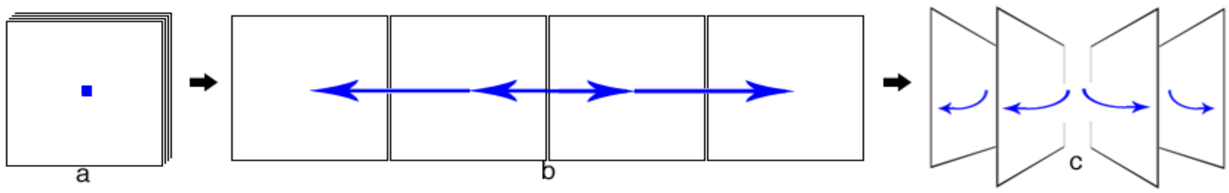

Figure 5. Sketch of transitions between different views: (a) superimposition, (b) juxtaposition, (c) two-and-a-half- dimensional.

section 4.1) and provide a common context for the interactive exploration of the three views. In order to do so, we designed an interaction metaphor and developed a set of smoothly animated transitions between views (Fig. 5). According to this metaphor, the planes onto which the diagrams are drawn are rendered as transparent sheets. They are stacked upon each other in the superimposition view (Fig. 5.a), then translated alongside the time axis in juxtaposition view (Fig. 5.b), and finally rotated by 90 degrees around their vertical axes in the two-and-a-half dimensional view (Fig. 5.c).

In our prototypical implementation, we used the *Prefuse* visualization toolkit [27] for the interactive visualization of diagrams on planes, and the Java binding for the OpenGL API (JOGL)[1] for developing the three views and the transitions between them in three-dimensional space.

4.3 SNA integration

As mentioned in section 2, the integration of analytical methods with visualization and interaction techniques can support and enhance the comprehension of network data. As a first step towards the combination of visual and analytical methods, we considered classic SNA metrics for static (i.e., non-temporal), single-relational networks and integrated their computation into our prototype. In this way, a user can interactively select a certain SNA metric to be computed for a certain type of relation s/he is interested in. The entire temporal multi-relational network is partitioned into as many static single-relational networks as there are time slices and the requested metric is computed for each of them. Then, the resulting values are mapped to visual variables in the visualization (color, size, etc.) for each time slice. In Figure 4, for example, the eigenvector centrality is mapped to node color. In general, this integration supports the analysis by enriching the node-link diagram with the values of global and local topological properties. It also enables the tracking of the network evolution through the trend of its analytical measures as explained in the following section.

4.4 Trajectories

While it is important to analyze and understand the topology of the network, in other words its relational structure (i.e., its edges), nodes are just as important, representing the actors of all the social interaction. Therefore, a good visual analytics approach supporting dynamic network analysis should stress the node properties and the changes they undergo over time. In particular, given the importance we give to the layout and the information it conveys, we should provide users with a mechanism to track a node over time and to find its position in each time slice in a more immediate way than by just preserving stability. We accomplished this requirement by showing the node trajectories with an adequate interaction technique for each view.

In the case of the superimposition view, we get an obvious solution from our dynamic chain layout: by simply displaying the special edges connecting the instances of a given node in different time slices, we obtain a polygonal chain that is exactly the trajectory of that node (Fig. 3). Unfortunately, the superimposition view is already cluttered with nodes and edges of all the time slices, and consequently edge crossing. Moreover, many visual variables that could have been used to differentiate trajectories from nodes are already exploited (color and bending to distinguish different types of relations, transparency to distinguish recent and old time slices). Thus, we allow users to alternatively visualize edges and trajectories or to visualize them only on demand. However, the fact that all nodes lie on the same plane region should provide some sort of a context that facilitates exploration and comparison even if not all edges and trajectories are displayed at the same time.

The lack of this proximity context, jointly with the persistence of the crossing of both edges and trajectories, makes it very cumbersome to exploit the trajectories in the juxtaposition view.

Conversely, the two-and-a-half-dimensional view is very well suited for the visualization of trajectories, which can link node instances in different time slices along the spatial dimension dedicated to time (Fig. 4). In this case, at least for certain datasets and tasks, it might be effective to also visualize all the trajectories at once. Moreover, in that spatial dimension there are visual variables to which we can map additional information. For instance, we can shade different colors along the trajectory of a given node to show how its values for a certain metric vary over time. In this way, the results of analytics methods are integrated directly into the main visualization of the network, enabling the user to examine its relational and temporal aspects simultaneously without any additional diagram. In the organizational network of Figure 4, we observe that “Pa” has constantly little importance (green trajectory) while “Je” has a very important role at the beginning but progressively loses it (trajectory shading from blue to green). Moreover, “Pa” increases her relations from six in the first time slice to eight in the last, while “Je” loses his relations till he remains connected to “Pa” only.

4.5 Dual-mode highlighting

The need to combine the analysis of the trajectory of any given node with the analysis of its ‘neighbors’ (adjacent nodes, i.e., those nodes to which it is directly connected in one step) led to the design of an additional interaction technique that can be referred to as a dual-mode highlighting. The dual mode relates to the way the graph is traversed and adjacent edges and nodes are highlighted on mouse over. In the first mode (Fig. 2.a) adjacent edges are traversed first when the user hovers over a node and the nodes that are connected to the selected node in the same time slice are found. Then, the trajectories of all these nodes are traversed. Thus, the same set of nodes is highlighted in each time slice, even if they are not adjacent in the other time slices. The

[1] http://jogamp.org/jogl/

second mode (Fig. 2.b) works the other way round: when the user hovers over a node, the graph is traversed with a trajectories-first criterion. First trajectories that lead to other instances of that node in other time slices are found, and then edges. Thus, all node instances that are adjacent to the correspondent instance of the selected node for each time slice are highlighted. By clicking on the selected node, the user can switch from one mode to the other according to her/his needs. The former mode, for example, might be useful to track the temporal evolution of a fixed group of nodes (the neighbors of the hovered one in the hovered time slice). In the example network (Fig. 2.a) we see that all persons that are connected to P.K. (the red node) in the first time slice, remain 'near' to her in the bigger group in the second time slice. The latter mode might help to follow the evolution of a single node and to explore the connections it establishes over time. In our example P.K. is directly connected with all of the four persons in her group in the first time slice. In the second time slice, she is directly connected with eight persons, but there are some persons in the bigger group to whom she has no relation (Fig. 2.b).

5. CONCLUSION AND NEXT STEPS

In this paper we have presented a visual analytics approach to explore and analyze dynamic social networks. We have discussed an interactive dynamic layout algorithm, outlined a possible integration of visual and analytical methods for dynamic networks, and introduced specific visualization and interaction techniques for task-specific exploration of dynamic networks. The main contribution is an approach to dynamic networks based on the integration of interactive visualizations with analytical methods (namely layout algorithms and graph-theoretical metrics) driven by basic perceptual principles.

Our future plans comprise an evaluation of our research prototype. Via user studies with both experts and non-experts we plan to validate our design and implementation choices. Then, we aim to carry out some improvements and extensions as for example exploring alternative representations besides node-link diagrams (e.g., matrix-based representations), further integrating visual and analytical methods, also going from static metrics and algorithms to dynamic ones. Finally, even if our design is confined to social networks and in particular organizational networks, some concepts and ideas might be applicable to dynamic networks in different contexts, in which both relational and temporal aspects are important and graph-theoretical algorithms are applicable and meaningful.

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