A Visual Analytics Technique for Identifying Heat Spots in Transportation Networks

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ABSTRACT

The public transportation system, as part of urban critical infrastructures, needs to increase its resilience. For doing so, decision makers need to understand the network itself and be aware of critical nodes. For doing so, we identified analysis tools for biological networks as an adequate basis for visual analytics. In the paper at hand we therefore adapt such techniques for transportation systems and demonstrate the benefits based on the Munich subway network. Here, visual analytics is used to identify vulnerable stations from different perspectives. The applied technique is presented step by step. We propose a network of networks analysis for the multiple vulnerable areas of the transportation system. Furthermore, the key challenges in applying this technique on transportation systems are identified. Finally, we propose the implementation of the presented features in a management cockpit for integrating the visual analytics mantra for advanced decision support on transportation systems.

Keywords: Transportation Network Analysis, Munich Subway Network, Network of Networks, Visual Analytics.

1. INTRODUCTION

The analysis of complex networks is an ongoing research field for various disciplines [1–3]. The concept of a complex network is used as a simplified frame of a complex system (e.g. a public transportation system). The nodes and the links of a network are represented by the entities and their interrelations in a system [4]. However, finding suitable visualization techniques for the structural information of complex networks is an open question [5].

Several studies showed so far the applicability of visual analytics in general [6–8] and to transportation systems in particular [9]. The paper at hand aims for developing a visual analytics technique to detect multiple vulnerable areas in a transportation network. This approach was already applied in bioinformatics to biological network analysis [10,11], but should not stay limited to this field of application. Transportation networks are often the target of disturbances and attacks, which makes knowledge about its vulnerability and resilience even more important. We therefore aim for applying the biological network analysis to the field of transportation networks in order to analyze and visualize critical spots.

In section 2, relevant features for transportation networks are identified. Methodological background, such as the visual analytics process and applied network analysis measures for transportation networks, is presented in section 3. In section 4 the Munich subway network is used as an example to apply the proposed visual analytics technique. Thereby, several visual representations according to different measures are presented.

Section 5 presents the key challenges of this technique and a final conclusion.

2. FROM BIOLOGICAL NETWORKS TO TRANSPORTATION NETWORKS

For transforming the analysis of biological networks to transportation networks, we first have to define their main characteristics and differences. Compared to biological networks, transportation networks tend to be smaller. While biological networks can have several million nodes, the world-wide air transportation network has 1.000 nodes and 35.000 links [12]. The considered network in this paper, the Munich subway network has 100 nodes and 198 links [13]. This leads to the fact that the visualization of a transportation network is rather focused on information visualization than on network drawing. The network drawing is more oriented on the visual representation, while the information visualization is more oriented on operating the network hierarchies for various view perspectives and interactions between its nodes.

Compared to biological networks, the visualization of transportation networks tends to be more subjective. This holds especially for the purpose of gaining information and knowledge for decision making. Thereby, nodes and links in transportation networks can be associated with costs and/or causalities. Therefore, the loss or damage of just one can be very significant in such networks [14].

While most biological networks are time independent, analyzing a transportation network, e.g. in terms of passengers’ flow, train traffic, financial revenues/losses, particular vulnerabilities, etc., is preferred to be studied on a time base. For example, the time window when a node reaches its maximum value in terms of passengers’ flow. Also, when studying for example the network reliability, route alternatives, or the shortest path of a route, more information needs to be considered for transportation networks. Besides the length of a link, e.g. also the availability of trains on that link need to be assessed [14]. When visualizing a transportation network as a directed network, the weights can store various information, e.g. the weights representing the number of trains traveling from one station to another in a subway network. These values are related to the nodes’ degree. Therefore, when considering parts of network with only one subway line, the number of trains varies in a small range, while for hub areas where the stations are crossed by more than one subway line, the number of trains increase significantly with the number of subway lines.

The connectivity of a transportation network is rather loose compared to most biological networks. For most of the world-wide subway networks it would be enough to lose one single node, or one link, in order to disconnect the whole network [15].
3. BACKGROUND

Visualization, as a science, is mainly dealing with visualization techniques for an efficient interaction. Branch of this science is the information visualization. This one refers to the visualization of abstract data with no explicit spatial references available [16]. In the last decade, an interdisciplinary version of visualization arose: visual analytics. The reason therefore is the strong need of understanding, and therefore also visualizing, huge amounts of data. Visual analytics is an adapted version of information visualization which combines advanced data analysis algorithms. Therefore, it can be defined as “an integral approach to decision-making, combining visualization, human factors and data analysis” [17].

The visual analytics process is described as an adaptive process [9], where the user can be rather involved in the visual data exploratory loop, or to the automated data analysis loop. The process itself is applied to assessing transportation networks in Section 4.

The network analysis combined with visual analytics is a key element for a proper understanding of a network. Classical network topology parameters can offer important structural information of the analyzed networks. These are recognized as relevant for network vulnerability measures [18,19]. Topology parameters, such as the number of nodes and links, diameter, network connectivity, girth, nodes and links connectivity, and cohesion, are compiled components for heuristic reliability indexes [20]. These indexes offer a quicker and insightful overview of the entire network vulnerability. This type of analysis was already conducted on transportation networks [15].

Structural measures, such as network entropies, can be considered as reliable measures to determine the structural properties of a network [21]. These measures capture the information structure of the complete neighborhood and the centrality properties of each node in the network [22]. Entropy measures have been successfully applied on transportation networks by using this information-theoretic method [23]. In this paper we refer to the recently introduced flow-weighted efficiency measure [14]. This measure calculates the efficiency of a transportation network by assessing two metrics weights: the length of links and the train traffic on each link. The most efficient nodes are here considered as being most vulnerable, as losing their regular flow results in a serious disturbance regarding the serviceability of the network [14]. We therefore propose applying the visual analytics technique to the flow-weighted efficiency measure. This enables the detection of network vulnerabilities from different visual perspectives: modularity, distances, train flow, and efficiency.

4. APPLICATION: MUNICH SUBWAY NETWORK

The visual analytics process is applied to the Munich subway network. This is encoded as an adjacency matrix for a directed network. The subway network consists of 100 stations as nodes, and 198 connections between stations as links [13].

In this work we consider the train traffic between every two linked stations in both directions on a daily basis. The collected numbers are public and available at http://www.mvvmuenchen.de. The selected schedule is based on the weekday schedule for business days between Monday and Thursday. However, results might differ for the other schedules available.

For visualization, we follow the visual analytics mantra “Analyze first, Show the Important, Zoom, filter and analyze further, Details on demand” [25]. Therefore, the focus is on a clear representation of the network. The nodes are the key of our visual analysis. The selected visualization layout is Reingold Tilford’s [26] which is a tree-like layout. In this case some cycles of the network might be omitted. Figure 1 is a simple representation of the network as directed graph with the selected visualization layout. The plots in this paper are generated with the RStudio [27] software and the igraph [28] package.

![Figure 1. A simple tree-like visual representation of the Munich subway network.](image-url)
More insights on the placement of nodes according to the other nodes can be seen from a modular perspective, which is illustrated in Figure 2. A module contains a connected subgroup of nodes of the network selected on different criteria. In this case, the nodes are grouped based on the available connections between them. Two different types of groups can be spotted. The small ones highlight the linear paths of subway lines, while the big ones highlight the presence of hub nodes. The latter are the key nodes of the network. The big groups show their impact in the network in terms of connectivity. Hub nodes like Innsbrucker Ring, Kolumbusplatz, Hauptbahnhof (for the lines U1, U2, U7, U8), Münchener Freiheit and Implerstraße can be spotted in the figure.

**Figure 2.** A modular tree-like visual representation of the Munich subway network.

**Figure 3.** Top five shortest (real) distances of the Munich subway network highlighted in a tree-like visual representation.
Another interesting analysis is the perspective of distances in the network. Figure 3 shows the top five shortest distances highlighted based on real life data [29]. The connections belong to the following groups of nodes: Josephsplatz - Theresienstraße 0.513 km, Hauptbahnhof (for the lines U4, U5) - Karlsplatz Stachus 0.521 km, Böhmerwaldplatz - Richard Strauß Straße 0.552 km, Silberhornstraße – Untersbergstraße 0.553 km, and Giselastraße - Münchner Freiheit 0.579 km.

In Figure 4 the top ten most demanded nodes in terms of train flow in the Munich subway network are highlighted for a weekday schedule. For this analysis the total number of trains stopped in a node per day are considered. The nodes with the highest daily train flow are:

- Innsbrucker Ring with 759 trains/day,
- Giselastraße with 719 trains/day,
- Implerstraße with 719 trains/day,
- Marienplatz with 719 trains/day,
- Odeonsplatz (lines U3, U6) with 719 trains/day,
- Sendlinger Tor (lines U3, U6) with 719 trains/day,
- Universität with 719 trains/day,
- Goetheplatz with 717 trains/day,
- Poccistraße with 717 trains/day,
- Sendlinger Tor (lines U1, U2, U7, U8) with 712 trains/day.

In Figure 4 a very demanded route can be observed in the network with eight consecutive nodes in the top ten selection. The other two nodes highlighted represent central node hubs of the network.

In the last visual perspective of Figure 5, the top results of the flow-weighted efficiency measure [14] are highlighted. This measure is a combined analysis from the shortest distance of any pair of nodes in a network and the minimum number of trains available on that route per day. Thus, the measure uses the exact data processed for Figure 3 and Figure 4.

The top ten highlighted nodes and their values from Figure 5 are:

- Giselastraße - 6.32,
- Münchner Freiheit - 6.32,
- Hauptbahnhof (lines U4, U5) - 5.86,
- Karlsplatz Stachus - 5.86,
- Implerstraße - 5.83,
- Poccistraße - 5.83,
- Marienplatz - 5.71,
- Odeonsplatz (lines U3, U6) - 5.71,
- Goetheplatz - 5.37,
- Universität - 4.91.
For profound managerial decision making each analysis might make sense and give additional insights into the network structure. This shows that applying measures from biology definitively makes sense for other fields of application, such as transportation networks. However, the special architecture and design of a transportation network demands for further improvements of the measures. To this end, the flow-weighted efficiency measure was found to be very helpful and allowing for deeper insights [13].

A more convenient solution than working with heat zones is the extraction of highlighted nodes. This would lead to a further step via creating another network: the network of networks. In this way, the last step of the visual analytics mantra “Details at demand” can be applied. More precisely, the network analysis measures presented in the previous section could now be applied on the exact parts of the network on which decisions must be focused. However, the procedure stays unchanged and follows the approach presented in the paper at hand.

5. CONCLUSION

The paper at hand might be seen as one more proof that the application of visual analytics is favorable for several disciplines and might support managerial decision making in various fields. As critical infrastructures in general, and the rail-bound public transport in special, are essential for the functioning of a society and are therefore often targets of (terroristic) attacks, we analyzed the systems vulnerability and identified the most important spots that need special treatment in terms of safety and security, as well as recovery after interruptions. Thereby we showed, that the combination of two different measures from biology can be used to gain deeper insights into the system’s serviceability.

However, there are several challenges in applying the visual analytics process on transportation networks. Concerning the analysis, it is an open gap to find the most suitable topologies for the structural interpretation of the networks. The same holds for visualization techniques for this type of networks. The solutions are rather subjective.

However, assessing multiple values of weights for links and the physical position of each node in relation to the others will improve the analysis of transportation networks. In this sense, the analysis will be more realistic when measuring classical topological measures, e.g. diameter, shortest path, or average path length. A physical position of the nodes can control the overlapping problem when plotting.

This type of analyzes can also be performed on a time base, being an extension from static networks to dynamic networks. Thereby, the most vulnerable spots of the transportation networks can be assessed for different time schedules.

In conclusion, visual analytics can be successfully applied to describe and visualize network structures and their vulnerabilities. However, decision makers do not have modelers available all the time. Therefore, we propose the automated analysis via the implementation of several measures for special types of networks, such as transportation networks, in a management cockpit. This integration of visual analytics into a novel decision support tool would allow for fast and detailed analyzes in special fields such as transportation networks. The integration into a management cockpit will be presented in a follow-up publication.
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