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Visual Stability in Dynamic Graph Drawings

Abstract: In graph visualizations, dynamic networks are a special challenge. A typical approach is visualizing the network at several points in time. Drawing these individual time slices often leads to changes in the layout that distract viewers from important information about individual nodes. In this article, we present a mathematical model to quantify the visual stability of dynamic graph drawings. The model takes into account structural and layout-oriented characteristics of the graphs. In order to validate the model, we conducted a study using questionnaires and an eye-tracking device. The participants were asked to track nodes in a dynamic network with three different methods. Then, we compared these methods based on the proposed model, user feedback (questionnaires) and behavioral data (eye-tracking). The results suggest that dynamic graph drawings which assign a fixed position on the canvas to every actor in the network improve the efficiency of the visual search. Nonetheless, more time is required to process the image. In contrast to that, those dynamic graph drawings with a constant shape or with a minimal number of changes require less time to process the image but lose efficiency of visual search.

Keywords: graph visualizations, dynamic graphs, visual stability, case study, eye-tracking

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1 Introduction

Dynamic networks are graphs characterized by the addition or removal of nodes and edges at different points in time [6]. These graphs are often produced by taking a successive sequence of “snapshots" from the network time line using a pre-specified *time window* [11]. This sequence of “snapshots” can be further used to create visual representations known as dynamic graph drawings [18]. However, there are certain issues when we use snapshots to create dynamic graph drawings. Each “snapshot" is drawn individually. This causes changes on the layout between different snapshots. Furthermore, nodes can leave the dynamic network without prior information. These factors can distract the user and affect the efficiency of visual search.

In this article, we study how visual stability may affect users who perform search tasks in dynamic networks. We propose a mathematical model to quantify the visual stability of dynamic graph drawings created from snapshots. Furthermore, we conducted a case study which combined user questionnaires and an eye-tracking device to record the participants’ activity. Fifteen students participated in the study. The participants were requested to track members of a software development community over five periods of time in three different scenarios. It was shown that on the one hand, users need less time to process information when we minimize structural and layout changes in dynamic graph drawings. On the other hand, search efficiency improves when we assign fixed positions to nodes. This indicates a trade-off between preserving visual stability and making important information easily identifiable.

The article is organized as follows. In section 2, we provide related work about visualization of dynamic networks. In section 3, we present the mathematical model of visual stability. We present the method of study in section 4 and the results in section 5. We discuss our findings in section 6 and present the conclusions in section 7.

2 Related work

2.1 Visualization of dynamic social networks

Sequences of snapshots have been widely used to visualize dynamic networks. For example, Forcoa.Net [12] is a web-based tool designed for the analysis and visualization of co-authorship networks over time. The system is mounted on top of the DBPL data set from computer science, containing information about 913,543 authors. Forcoa.Net can display the co-authorship network of specific authors, including statistical information about their collaboration, stability [14] and how they changed in each snapshot of the dynamic graph.

Weaver [10], combines sequences of snapshots with 2D and 3D perspectives to visualize dynamic social networks. The 2D perspective displays the nodes (actors) along with the edges (relations) in a single snapshot of the dynamic graph. These elements are placed over the canvas with the *simple space solution algorithm* [13]. The 3D perspective shows the overview of the snapshots in the dynamic graph. In addition, *Weaver* introduces a set of colored edges pinpointing a specific node over different snapshots.

An alternative with a similar functionality as *Weaver* is the *Visual Analytics Approach* [7]. This java-based application offers three different perspectives to track nodes (actors) in a dynamic social network. The first perspective presents a superimposition of all the elements from the dynamic graph in a single view. A selected actor is connected to other elements of the network through a set of polygonal chains, simulating their trajectory. The second perspective is composed by a juxtaposition. The user can select different snapshots from the dynamic graph and they will be aligned next to each other. Thus, it is possible to find similarities or differences in the graph at different points in time. The third perspective arranges the snapshots of the dynamic network in a in a "booklet" metaphor, using a two-and-a-half view. The trajectory of a single actor is illustrated as a line drawing going through all "pages" of the "booklet".

2.2 Layout adjustment techniques for dynamic graph drawings

A limitation of the snapshot strategy is that a graph drawing is computed independently for every snapshot in the sequence. As a result, nodes (actors) and edges (relations) can appear in different locations over the canvas during the exploration of the dynamic network. This may introduce changes that distract the user. Modern graph visualizations minimize the changes between the consecutive drawings. This is important because it helps users identify nodes easier and with less errors [1]. For example, drawings generated with a *Circular Layout* [19] have a shape that remains constant during the exploration of the dynamic network. Nonetheless, actors can change their positions over the circumference. Diehl [5] proposed several alternatives to reduce the dissimilarities in a sequence of graph drawings. *Predecessor dependent adjustment* proposes the generation of consecutive graph drawings by using the same structure as its predecessors. *Simultaneous adjustment* follows a similar approach by generating drawings based on the structure of the next graph in sequence. *Context dependent adjustment* proposes to generate the current drawing considering the structure of the predecessor and successor graphs in the sequence. The *independent adjustment* proposes to aggregate all the elements of the dynamic network into a global drawing and only display those parts that match the snapshot under exploration.

The *Foresighted Graph Layout* (*FGL*) [4] is a dynamic graph drawing algorithm which follows the independent adjustment. The algorithm initiates by aggregating the actors and relations of the dynamic graph into a global drawing. The global drawing is named *Super Graph* and assigns a fixed position on the canvas to each node of the dynamic network. This requires a lot of drawing space and, therefore, a reduction process is executed afterwards. *Lifetime* is an attribute describing the appearance of an actor or relation in the dynamic graph. A set of "containers" called *partitions* are used to store actors or relations. Thus, the actors that do not appear in the same snapshot can be placed into the same node partition. The same principle applies to the relations. All the relations with disjoint lifetimes can be placed together into the same edge partition. The partitions obtained from the compression process form the Foresighted Graph Layout, a drawing that not only requires less space to be drawn, but also that has the minimal number of changes on its structure. The FGL can be combined with other graph drawing algorithms. When a circular drawing is used together with the FGL, it results in a *Foresighted Circular Layout*. The constant structure of the Circular Layout, the fixed positions of the Super Graph, and the minimal changes on the drawing provided by the Foresighted Graph Layout are factors related to the stability in the visual perception [15, 16, 17].

3 A mathematical model of visual stability for dynamic graph drawings

We propose a model of visual stability in order to quantify structural and layout-oriented characteristics of dynamic graph drawings. The model defines nine quantitative measures to cover aspects such as detection of possible offsets between consecutive graph drawings and the changes due to the addition or removal of nodes.

A *graph* [21] is defined as $g = (V, E)$, where V is a set of vertices and E is a set of edges $E \subseteq V \times V$. Likewise, a graph drawing [20] d of a graph g is defined as a mapping of each vertex v from g to a distinct point $P(v) = (v_x, v_y)$ of a plane and each edge (u, v) from g to a simple Jordan Curve with end points $P(u)$ and $P(v)$. A straight line drawing is a drawing in which every edge is mapped to a straight line segment; more formally, a straight line drawing is an injective function $f : v \in V \to (v_x, v_y) \in \mathbb{R}^2$. These definitions served as the foundations of the model of visual stability. Nonetheless, the notion of a graph drawing was extended to cover approaches like the foresighted graph layout [4], in which multiple vertices are mapped to the same position.

- Let f_{pv} be the mapping of the vertices v of a graph g to a **vertex logical position** in the form:

$$f_{pv} : V \to P$$

  where P is a set in the form $\{p_1, p_2, p_3, ..., p_n\}$.
- Let f_{sv} be the mapping of the vertex logical positions to a two-dimensional Euclidean Space in the form:

$$f_{sv} : P \to \mathbb{R}^2$$

$$f_{sv}(p) = (f_{sv}(f_{pv}(v)) = (x, y)$$

- Let f_{pe}: be the mapping of the edges (u, v) of a graph g to an **edge logical position** in the form:

$$f_{pe} : E \to P \times P,$$

$$f_{pe}(e) = f_{pe}((u, v)) = (f_{pv}(u), f_{pv}(v))$$

- Let f_{se}: be the mapping of the edge logical positions to a two-dimensional Euclidean Space in the form:

$$f_{se} : P \times P \to \mathbb{R}^2 \times \mathbb{R}^2,$$

$$\begin{aligned} f_{se}(p_u, p_v) &= (f_{sv}(p_u), f_{sv}(p_v)) \\ &= (f_{sv}(f_{pv}(u)), f_{sv}(f_{pv}(v))) \\ &= ((x_1, y_1), (x_2, y_2)) \end{aligned}$$

Therefore, a **graph drawing** is defined as a mapping of the elements of a graph g to the Euclidean Space in the form:

$$d(g) = (f_{sv}(f_{pv}(V(g)), f_{se}(f_{pe}(E(g))))$$

3.1 Model-based measures

A **dynamic graph drawing** [4] in the form $D(G) = [d(g^1), d(g^2), d(g^3)..., d(g^n)]$ is considered to be visually stable if the changes during a transition ($d(g^i)$ to $d(g^{i+1})$ are minimal or null. The model of visual stability introduces nine measures to verify such condition.

3.1.1 Vertex set stability

The **vertex set stability** or **VS**, calculates the percentage of vertices from g^i that are present in g^{i+1} with the function:

$$VS = \frac{|V(g^i) \cap V(g^{i+1})|}{|V(g^i) \cup V(g^{i+1})|}$$

The values obtained for the **VS** are in a range from 0 to 1. Values closer to 0 suggest only a few vertices from g^i are present in g^{i+1}, while values closer to 1 indicate the opposite case.

3.1.2 Vertex set drawing stability

The **vertex set drawing stability** or **VDS**, calculates the percentage of **vertex logical positions** from $d(g^i)$ that are present in $d(g^{i+1})$ with the function:

$$VDS = \frac{|f^i_{pv}(V(g^i)) \cap f^{i+1}_{pv}(V(g^{i+1}))|}{|f^i_{pv}(V(g^i)) \cup f^{i+1}_{pv}(V(g^{i+1}))|}$$

The values obtained for the **VDS** are in a range from 0 to 1. Values closer to 0 suggest only a few vertex logical positions from $d(g^i)$ are present in $d(g^{i+1})$, while values closer to 1 indicate the opposite case.

3.1.3 Edge set stability

The **edge set stability** or **ES**, calculates the percentage of edges from g^i that are present in g^{i+1} with the function:

$$ES = \frac{|E(g^i) \cap E(g^{i+1})|}{|E(g^i) \cup E(g^{i+1})|}$$

The values obtained for the **ES** are in a range from 0 to 1. Values closer to 0 suggest only a few edges from g^i appear in g^{i+1}, while values closer to 1 indicate the opposite case.

3.1.4 Edge set drawing stability

The **edge set drawing stability** or **EDS**, calculates the percentage of **edge logical positions** from $d(g^i)$ that are present in $d(g^{i+1})$ with the function:

$$EDS = \frac{|f_{pe}^{i}(E(g^i)) \cap f_{pe}^{i+1}(E(g^{i+1}))|}{|f_{pe}^{i}(E(g^i)) \cup f_{pe}^{i+1}(E(g^{i+1}))|}$$

The values obtained for the **EDS** are in a range from 0 to 1. Values closer to 0 suggest only a few edge logical positions from $d(g^i)$ appear in $d(g^{i+1})$, while values closer to 1 indicate the opposite case.

3.1.5 Vertex set degree change

The **vertex set degree change** or **VDC**, calculates the variations on the degree (i.e. number of connections) of those vertices from g^i that are present in g^{i+1} with the function:

$$VDC = \frac{\sum_{v \in V(g^i) \cap V(g^{i+1})} \left| \frac{C_d^i(v)}{|V(g^i)|} - \frac{C_d^{i+1}(v)}{|V(g^{i+1})|} \right|}{|V(g^i) \cap V(g^{i+1})|}$$

where C_d^i stands for the **degree centrality** [21] of a vertex v in g^i. The values for the **VDC** are in a range from 0 to 1. Values closer to 0 suggest a minimal change on the degree centrality for those nodes appearing in g^i and g^{i+1}, while values closer to 1 indicate the opposite case.

3.1.6 Vertex set drawing neighborhood change

The **vertex set drawing neighborhood change** or **VDNC**, calculates the variations on the number of connections for those vertex logical positions from $d(g^i)$ that are present in $d(g^{i+1})$ with the function:

- Let $PV^i = f^i_{pv}(V(g^i))$
- Let $PE^i = f^i_{pe}(E(g^i))$
- Let $V^* = PV^i \cap PV^{i+1}$

$$VDNC = \frac{\sum_{v \in V^*} \left(\left| \sum_{e \in PE^i} \frac{f_c(v,e)}{|PV^i|} - \sum_{e' \in PE^{i+1}} \frac{f_c(v,e')}{|PV^{i+1}|} \right| \right)}{|V^*|}$$

where f_c is a function in the form

$$f_c : P \times (P \times P) \rightarrow [0,1]$$

$$f_c : (p1,(p2,p3)) = \begin{cases} 1, & \text{if } p1 = p2 \\ 1, & \text{if } p1 = p3 \\ 0, & \text{otherwise} \end{cases}$$

The values obtained for the **VDNC** are between 0 and 1. Values closer to 0 suggest a small change on the number of connections for those vertex logical positions appearing in $d(g^i)$ and $d(g^{i+1})$, while values closer to 1 indicate the opposite case.

3.1.7 Vertex set drawing active positions

The **vertex set drawing active positions** or **VDAP**, calculates the percentage of **vertex logical positions** that are active in $d(g^i)$. The indicator was designed for those dynamic graph drawings using a global layout, rather than techniques computing a sequence of independent drawings. The **VDAP** is defined as:

$$VDAP = \frac{|f^i_{pv}(V(g^i))|}{|\cup^n_{i=1} f^i_{pv}(V(g^i))|}$$

In case the drawing technique computes a sequence of independent drawings, the **VDAP** is defined as:

$$VDAP = \frac{|f^i_{pv}(V(g^i))|}{|f^i_{pv}(V(g^i))|} = 1$$

The values obtained for the **VDAP** are in a range between 0 and 1. Values closer to 0 indicate a small number of vertex logical position are active in the current drawing, while values closer to 1 indicate the opposite case.

3.1.8 Edge set drawing active positions

The **edge set drawing active positions** or **EDAP**, calculates the percentage of **edge logical positions** that are active in $d(g^i)$. The indicator was designed for those dynamic graph drawings using a global layout, rather than techniques computing a sequence of independent drawings.
The **EDAP** is defined as:

$$EDAP = \frac{|f^i_{pe}(E(g^i))|}{|\cup_{i=1}^{n} f^i_{pe}(E(g^i))|}$$

In case the drawing technique computes a sequence of independent drawings, the **EDAP** is defined as:

$$EDAP = \frac{|f^i_{pe}(E(g^i))|}{|f^i_{pe}(E(g^i))|} = 1$$

The values obtained for the **EDAP** are in a range between 0 and 1. Values closer to 0 indicate a small number of edge logical position are active in the current drawing, while values closer to 1 indicate the opposite case.

3.1.9 Graph drawing offset

The **graph drawing offset** or **GDO**, calculates the changes on the coordinates of those vertex logical positions that have been mapped to the Euclidean Space.
- Let $f^i_{mv} = f^i_{sv}(f^i_{pv}(V(g^i))$ be the mapping of the vertices of $d(g^i))$ to the Euclidean space.

Thus, the **GDO** is defined as:

$$GDO = \sum\nolimits_{v \in V(g^i) \cap V(g^{i+1})} dist(f_{mv}(v)^i, f_{mv}(v)^{i+1})$$

where *dist* refers to the *euclidean distance* between two points. The values obtained for the **GDO** are higher or equal to 0. Lower values of **GDO** suggest minimal variations on the coordinates of those vertex logical positions present in in $d(g^i)$ and $d(g^{i+1})$, while higher values indicate drastic changes on the coordinates of these elements.

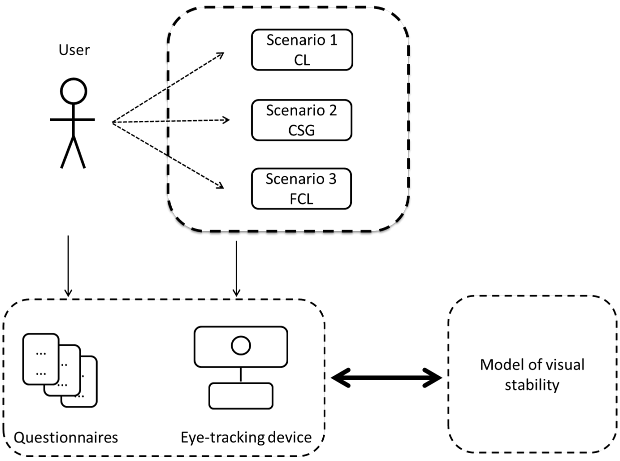

Fig. 1. A case study for the validation of the model of visual stability

4 Method of the study

4.1 Study setup

In order to validate the model of visual stability, we conducted a case study. We used questionnaires to gather information about the user experience, an eye-tracking device to record the eye movements of the participants and the model to quantify the visual stability of the dynamic graph drawings. An overview of the method of study is illustrated in Figure 1. The case study consisted of three scenarios. Each one of them displayed a dynamic network using different dynamic graph drawings: a *Circular Layout* (CL), a *Circular Super Graph* (CSG) and a *Foresighted Circular Layout* (FCL), as described in Section 2.2. *Scenario 1* made use of the CL. The technique was selected because it provides a drawing with a *constant shape* during the exploration of the dynamic network. However, it changes the positions of the nodes to maintain the shape. *Scenario 2* made use of the CSG. The technique was selected because it assigns a *fixed position* to each actor in the dynamic network. The drawing does not maintain a constant shape. *Scenario 3* made use of the FCL. The FCL was selected because it assigns a *fixed position* to each actor in the dynamic network and, at the same time, it has a *minimal number* of structural changes. The FCL allows several actors to occupy the same position in different points in time. Each participant went through the scenarios in random order.

A group of fifteen students of computer science and applied cognitive science, from 22 to 28 years-old, participated in the study. The participants had basic knowledge regarding network analysis techniques. The students were asked to complete a series of search tasks in different scenarios. The visualized dynamic network [22] was extracted from the developer mailing list of the Asterisk open source project and contained five snapshots. Each snapshot represented a month of communication between the developers. The developers were represented as nodes and the e-mails they exchanged as edges. The research hypothesis was that *visually stable drawings improve search efficiency and user experience while tracking actors in a dynamic network*. There was no time limit for the completion of the scenarios. Yet, the average duration per student for all three scenarios was 30 minutes.

4.2 Questionnaires

After completing the tasks, the students were asked to fill in a questionnaire about their experience with the different drawings. Each question was rated on a five point Likert scale, where 1 indicated strong disagreement and 5 indicated strong agreement. The criteria under evaluation are listed next:

- **C1** : The drawing technique uses fixed positions for persons.
- **C2** : The drawing technique is useful to track persons in a dynamic graph.
- **C3** : The changes on the drawing are noticeable.
- **C4** : The drawing technique requires some effort to locate a person.
- **C5** : The addition or removal of entities from the drawing is distracting.
- **C6** : The addition or removal of relations from the drawing is distracting.

Criteria C1 and C2 are positive criteria. Criteria C3 to C6 are negative criteria.

4.3 Eye-tracking

We analyzed the eye-tracking data with metrics that have been proven to measure cognitive load and search efficiency during search tasks [8, 2, 9]. The metrics used in the study are shown in Table 1. These metrics were applied on the overall drawing area and on particular areas of interest (AOI's), i.e. where the target of the search (actor) was located (Figure 2. The AOIs did not maintain a fixed position for all the drawing techniques.

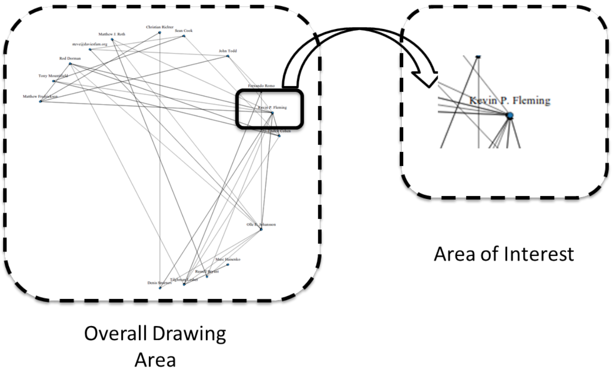

Fig. 2. Overall drawing area and example for an area of interest

Metric	Description
Number of fixations	Number of times a user fixates elements
Duration of fixations	Average time spent on fixations
Number of saccades	Number of saccadic movements performed
Duration of saccades	Average time spent on saccadic movements
Saccadic amplitude	Distance covered during saccadic movements
Scan path length	Average distance covered between successive fixations by saccades (scan paths)
Scan path duration	Average time spent on scan paths
Spatial density	The spatial distribution of gazepoints on the screen
Fixation/Saccade ratio	Ratio comparing the time spent on processing elements to the time spent on searching for elements
Time to first fixation	Average time spent to locate an element for the first time
Fixations on target	Number of fixations appearing on a specific target

Table 1. Eye tracking metrics used for purpose of the analysis

5 Analysis and results

5.1 Model of visual stability

The measures of the model were computed for the individual transitions between snapshots of the three scenarios presented in the study and averaged. This gave us an indication of the overall visual stability of the dynamic graph drawings. The results are illustrated in Table 2.

The *Foresighted Circular Layout* (FCL) and the *Circular Super Graph* (CSG) rely on a global layout to minimize the changes in the dynamic graph drawing. Thus, they have a lower number of active positions in comparison to the *CL*, which relies on an independent sequence of graph drawings. The *FCL* had 48% (0.485) of the vertex logical positions (VDAP) and 14% (0.143) of the edge logical positions as active. The CSG had 19% (0.198) of the vertex logical positions (VDAP) and 11% (0.112) of the edge logical positions as active. For the *Circular Layout* (CL) all vertex (VDAP) and edge (EDAP) logical positions were active. The dynamic graph drawings also presented dissimilarities with respect to the offset of the elements on the canvas, as shown by the graph drawing offset (GDO). The *FCL* and the *CSG* presented 0% GDO because both approaches map each vertex logical position to a fixed location in the Euclidean Space. In contrast, the *CL* maps the vertex logical positions to a different location in each snapshot. Therefore, the GDO for the *CL* was 2564.68.

The *CL* had a vertex set stability (VS) and a vertex set drawing stability (VDS) of 16% (0.165). The edge set stability (ES) and the edge set drawing stability (EDS) were 1% (0.015). The same result was found for the *CSG*. The *FCL* had a vertex set stability (VS) of 16% (0.165) but a vertex set drawing stability (VDS) of 49% (0.493). The edge set stability (ES) was 1% (0.015) while the edge set drawing stability (EDS) was 4% (0.043). Furthermore, the vertex set drawing neighborhood change (VDNC) was 0.40% (0.403) for the *FCL* while the *CSG* together with the *CL* had 41% (0.413). This suggests the *FCL* maintains more elements on the screen, despite the graph changes.

Model-based quantitative measures	CL	CSG	FCL
Vertex set drawing active positions (VDAP)	1.000	0.198	0.485
Edge set drawing active positions (EDAP)	1.000	0.112	0.143
Graph drawing offset (GDO)	2564.683	0.000	0.000
Vertex set stability (VS)	0.165	0.165	0.165
Vertex set drawing stability (VDS)	0.165	0.165	0.493
Edge set stability (ES)	0.015	0.015	0.015
Edge set drawing stability (EDS)	0.015	0.015	0.043
Vertex set drawing neighborhood change (VDNC)	0.413	0.413	0.403

Table 2. Average visual stability calculated for the three drawings under study

5.2 Questionnaires

The data collected from the questionnaires provided an insight about the user experience in the different scenarios. We computed the average values of the user ratings per criterion. The user ratings lie within [1, 5], (mean value = 3). We present the average user rating for criteria 1 and 2 in Figure 3. Criteria 1 and 2 are positive, therefore a 5 is perceived as the best rating while 1 is perceived as the worst. In Figure 4 we present the average user rating for criteria 3 to 6. These criteria are perceived as negative, therefore 5 is the worst score while 1 is the best.

Scenario 1 presented the dynamic network with the *Circular Layout* (CL). The average duration of the scenario was *09:14* minutes. The CL was rated negatively despite its constant shape. The students did not notice that the actors were assigned to fixed positions in the Euclidean Space (C1 = 2.467). Furthermore, the changes on the drawing were noticeable (C3 = 3.267) and it was difficult for students to locate the actors in question (C4 = 3.267). Nonetheless, the addition and removal of elements from the drawings did not distract the students (C5 = 2.533, C6 = 2.533). Still, the students did not find the *CL* useful for tracking actors in a dynamic network (C2 = 2.667).

Scenario 2 presented the dynamic network with the *Circular Super Graph* (CSG). The average duration of the scenario was *09:11* minutes. The students noticed that the actors were maintaining their position on the drawing (C1 = 3.400) and the effort to locate them was reduced in comparison to the *CL* (C4 = 2.733). The changes on the drawing were still noticeable (C3 = 3.067). The addition and removal of elements was distracting during the execution of the tasks (C5 = 2.667, C6 = 2.667). Despite this fact, the use of fixed positions

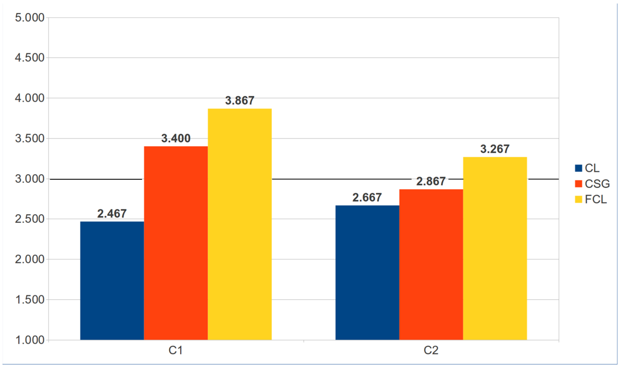

Fig. 3. Results of the user questionnaires for positive criteria (C1, C2)

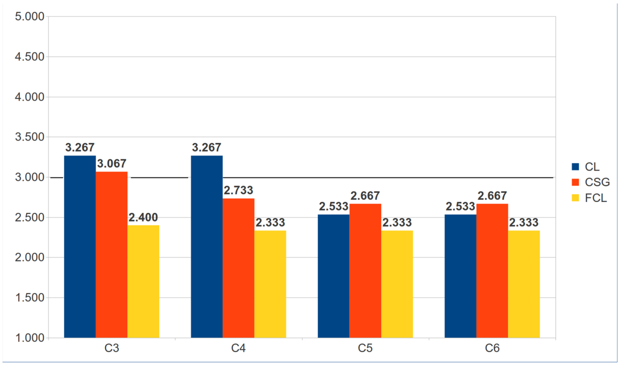

Fig. 4. Results of the user questionnaires for negative criteria (C3-C6)

improved the usefulness of the drawing technique (C2 = 2.867).

Scenario 3 presented the dynamic network with the *Foresighted Circular Layout* (FCL). The average duration of the scenario was *09:09* minutes. The students noticed that the actors were mapped on fixed positions in the Euclidean Space (C1 = 3.867). The effort to locate an actor with the *FCL* was lower in comparison to the *CSG* and the *CL* (C4 = 2.333). The changes on the drawing were not prominent (C3 = 2.400), while the distraction produced by the addition or removal of elements from the drawing was reduced (C5 = 2.333, C6 = 2.333). In general terms, the students considered the *FCL* as the most useful technique to track actors in a dynamic network (C2 = 3.267).

5.3 Eye-tracking metrics on the overall drawing area

The data collected from the eye-tracking device provided further insight regarding the visual search and the recognition of elements. The results are presented in Table 3. The *Circular Super Graph* (CSG) had the minimal number of fixations (OFIX1 = 64.080). The duration of fixations was the longest (OFIX2 = 0.289 seconds) compared to the *Circular Layout* (CL) ($[Z = -3.010, p = .003]$) and the *Foresighted Circular Layout* (FCL) ($[Z = -2.158, p = .031]$). A similar pattern was observed for the saccades. The *CSG* had the minimal number of saccades (OSAC1 = 64.347) but their duration was the longest (OSAC3 = 0.041 seconds) for the three drawing techniques. For the saccadic amplitude, the *FCL* was the technique with the lowest value (OSAC2 = 121.689 pixels) in comparison to the *CL* ($[Z = -2.840, p = .005]$) and the *CSG* ($[Z = -2.385, p = .017]$).

The *CSG* had the shortest average scan path (OSCN1 = 3041.666 pixels), followed by the *FCL* (OSCN1 = 3173.70 pixels) and the *CL* (OSCN1 = 3441.96 pixels). However, the lowest value for the scan path duration was measured for the *CL* (OSCN2 = 6.446 seconds). A similar behaviour was observed for the spatial density. The *CSG* had the lowest spatial density (OSD1 = 0.355), followed by the *FCL* (OSD1 = 0.383, $[Z = -2.212, p = .027]$) and the *CL* (OSD1 = 0.437, $[Z = -3.413, p = .001]$). According to Goldberg [8] and Cowen [3], a low spatial density indicates efficient visual search. Furthermore, we calculated the fixation/saccade ratio (OFS1). High ratios indicate efficient search. The smallest ratio was found in the *CL* (OFS1 = 8.420) while the highest ratio was observed in the *FCL* (OFS1 = 10.126).

Eye-tracking metric	CL	CSG	FCL
Number of fixations (OFIX1)	**81.787**	**64.080**	**70.453**
Duration of fixations in seconds (OFIX2)	**0.234**	**0.289**	**0.267**
Number of saccades (OSAC1)	**82.413**	**64.347**	**71.067**
Saccadic amplitude in pixels (OSAC2)	**140.329**	**139.095**	**121.689**
Saccade duration in seconds (OSAC3)	**0.039**	**0.041**	**0.036**
Scan path length in pixels (OSCN1)	**3441.962**	**3041.666**	**3173.702**
Scan path duration in seconds (OSCN2)	**6.446**	**6.856**	**6.968**
Spatial density (OSD1)	**0.437**	**0.355**	**0.383**
Fixation/Saccade ratio (OFS1)	**8.420**	**9.444**	**10.126**

Table 3. Average value of the eye-tracking metrics for the overall drawing area.

5.4 Eye-tracking metrics on the areas of interest

On the areas of interest (AOIs), we applied two metrics: the number of fixations on target and the time to first fixation. The results are presented in Table 4. The *CSG* was the drawing technique with the highest number of fixations on target (AFOT1 = 0.038), followed by the *FCL* (AFOT1 = 0.037) and the *CL* (AFOT1 = 0.019). According to Goldberg [8], a high number of fixations on target indicates accurate visual search. The shortest time to first fixation was observed for the *CL* (ATTF1 = 1.688), while the longest time was observed for the *CSG* (ATTF1 = 3.283). High values of time to first fixation indicate a possible delay or potential difficulty to find an element [2].

Eye-tracking metric	CL	CSG	FCL
Number of fixations on target (AFOT1)	**0.019**	**0.038**	**0.037**
Time to first fixation in seconds (ATTF1)	**1.688**	**3.283**	**2.019**

Table 4. Average value of the eye-tracking metrics for the areas of interest.

6 Discussion

The model of visual stability aims to quantify structural and layout-oriented characteristics of dynamic graph drawings. The core rationale is to provide quantitative measures that reflect the amount of changes in dynamic graph drawings. We argue that such changes distract users when exploring dynamic networks visually. Furthermore, it is crucial to support search efficiency and to help users identify important information. This is a trade-off that we face, i.e. how to make crucial information more prominent while keeping the visual output stable. In order to gain further insight about the effects of visual stability in a dynamic graph drawing, we combined and analyzed subjective assessments (user questionnaires) and behavioral data (eye tracking data).

The *Circular Layout* (CL) had the highest value of graph drawing offset (GDO) since the nodes can change their position during the exploration of the dynamic network. The users had difficulties in this scenario and reported that they had to invest effort into tracking the actors in question. This was reflected in the eye-tracking metrics, i.e. long scan paths and low fixation/saccade ratio. Furthermore, the length of the scan paths was positively correlated with the criterion C4 (*"...requires some effort to locate a person"*) ($\rho = 0.516, p < 0.05$). The duration of the saccades was found to be positively correlated with the criterion C5 (*"The addition or removal of entities from the drawing is distracting"*) ($\rho = 0.539, p < 0.05$) and C6 (*"The addition or removal of relations from the drawing is distracting"*) ($\rho = 0.539, p < 0.05$). The fixation/saccade ratio, which compares the time spent processing elements with the time spent searching for them, was found to be negatively correlated to the criteria C5 ($\rho = -0.522, p < 0.05$) and C6 ($\rho = -0.522, p < 0.05$). This is an indication that the addition and removal of elements affects the efficiency of the visual search negatively.

The *Circular Super Graph* (CSG) mapped each actor in the dynamic network to a fixed position in the Euclidean Space. Therefore, the graph drawing offset was zero (GDO $=$ 0). The users liked the use of fixed positions and reported that it was easier to locate the actors in question. This was reflected in the eye-tracking metrics, i.e. high number of fixations on target, which indicates accurate visual search [8]. However, the duration of the fixations was the longest of all three cases, indicating that a lot of time is required to process an element [8].

The *Foresighted Circular Layout* (FCL) mapped several actors of the dynamic network to the same position in the Euclidean Space at different points in time. Therefore, the graph drawing offset was zero (GDO $=$ 0). The users rated the FCL as the most useful drawing technique for tracking nodes in dynamic graph drawings. The duration of the saccades was found to be negatively correlated with the C2 (*"The drawing technique is useful to track persons in a dynamic graph"* ($\rho = 0.649, p < 0.05$), while the fixation/saccade ratio correlated positively with the same criterion ($\rho = 0.598, p < 0.05$). As it is reported by Goldberg [8], saccades with short duration indicate search efficiency. However, a high fixation/saccade ratio indicates high processing time. Although the features of the *FCL* were rated as useful for tracking actors in a dynamic network, this does not necessarily mean that the time they need to process information is low.

The model of visual stability can be used for the development and evaluation of dynamic graph drawing algorithms in order to address the trade-off between search efficiency and visual stability. However, there are some points that we should further consider and elaborate with respect to the model usage. The approach was designed to operate with dynamic graph drawings created from sequences of snapshots. Therefore, it is not possible to provide information about the accuracy of the visual search, the processing time or the user experience in other visual metaphors. Furthermore, the proposed model can be used as a basis for a more general model that covers the trade-off between visual stability and highlighting structural changes of importance in dynamic networks. Visual stability is a property which unveils interesting characteristics of a dynamic graph drawing and we are just starting to explore its applications in dynamic networks

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7 Conclusions

In this article, we explored how visual stability affects users as they track actors in a dynamic network. To this end, we proposed a mathematical model to quantify the visual stability of a dynamic graph drawing. We further validated our approach through a case study with the use of questionnaires and eye-tracking data. The results suggest that the *Circular Layout* which is a dynamic graph drawing technique resulting a constant shape, does not provide a good user experience nor an efficient visual search because the positions of the actors in the Euclidean Space change. The *Circular Super Graph*, which maps every actor in the dynamic network to a fixed position in the Euclidean Space, improves the accuracy of the visual search. However, more time is required to process the image. The *Foresighted Circular Layout*, which maps several actors to the same position in the Euclidean Space in different points in time, improves the time required to process the image but leads to more extensive visual search compared to the CSG. However, the users rated the FCL as the most useful dynamic graph drawing technique to track actors in dynamic networks.

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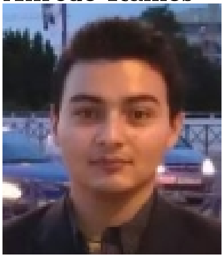

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