Human-centered Evaluation of 3D Radial Layouts for Centrality Visualization

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ABSTRACT

In this paper we propose improvements to the 3D radial layouts that make it possible to visualize centrality measures of the nodes in a graph. Our improvements mainly relate edge drawing and the evaluation of the 3D radial layouts. First, we projected not only the nodes but also the edges onto the visualization surfaces in order to reduce the node overlap that could be observed in previous 3D radial layouts. Secondly, we proposed a human-centered evaluation in order to compare the efficiency score and the time to complete tasks of the 3D radial layouts to those of the 2D radial layouts. The evaluation tasks proposed are related to the central nodes, the peripheral nodes and the dense areas of a graph. The results showed that 3D layouts can perform significantly better than 2D layouts in terms of efficiency when tasks are related to the central and peripheral nodes, while the difference in time is not statistically significant between these various layouts. Additionally, we found that the participants preferred interacting with 3D layouts over 2D layouts.

Keywords

3D Graph Visualization, Centrality Visualization, Graph Layout Evaluation.

1 INTRODUCTION

Centrality measures are topological measures that describe the importance of the nodes in a graph. There has been a lot of works carried out in this topic for network analysis in order to answer the question "Which are the most important nodes in a graph?" [Martino06, Yousefi20]. Other works in graph drawing chose to visually reveal these properties in order to facilitate their exploratory analysis [Brandes11, Raj17]. For example, in graph analytics, some works are interested in understanding and describing the interaction structure by analyzing the topology of the graph [Saqr18, Elmouden20]. Others are interested in identifying and characterizing the nodes that are particularly important in terms of topological position in a graph [Wang17] and how their neighbors are connected to each other [Zhang17].

However, visualizing these measures in 2D could be difficult when the size of the graph is important in terms of the number of nodes and edges. Indeed, there would be a lot of node and edge overlap and edge crossings, which are less of a problem in 3D than 2D [Teyseyre09]. Kobina et al. [Kobina20] therefore proposed new 3D methods based on the 2D radial layouts that highlight the centrality of the nodes [Brandes11] by optimizing the spatial distribution of the nodes. Nevertheless, in 3D some edges could hide others depending on the position of the observer or the 3D layouts and they did not analyze the relevance of their proposed methods.

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Our analysis of the state of the art encourages us to pursue this 3D approach by improving the existing one and comparing it to its 2D equivalent. This is why we first propose improvements to the 3D radial layouts by projecting not only the nodes but also the edges onto the visualization surfaces in order to reduce the node overlap. The purpose of our improvements is to provide a better overall view of a complex and large graph than the 3D radial techniques and to reduce the time in exploring and analyzing such a graph. We then propose a human-centered evaluation using a well-known centrality measure in order to compare the efficiency score and the time to complete tasks of the 3D radial layouts to those of the 2D radial layouts. The evaluation tasks are related to the central nodes, to the peripheral nodes and to the dense areas of a graph. The purpose of our evaluation is to show that the 3D radial methods could be better to explore and to analyze graphs whatever the interest, compared to the 2D radial layouts.

This paper is structured as follows: in section 2 we recall some notions about centrality measures in graphs.

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We review related work on centrality visualization in section 3. We then present our improvements in section 4 and the human-centered evaluation of these improvements in section 5. In section 6 we present the evaluation results while in section 7 we present our discussion of the various results. In section 8 we present our conclusion and we finally present our future work in section 9.

2 CENTRALITY MEASURES IN GRAPHS

In graph analytics, centrality measures [Saxena20] characterize the topological position of the nodes in a graph. In other words, centrality measures make it possible to identify important nodes in the graph and further provide relevant analytical information about the graph and its nodes.

Some centrality measures, such as degree centrality, can be computed using local information of the node. The degree centrality quantifies the number of neighbors of a node. On the other hand, Betweenness centrality and closeness centrality [Freeman77, Freeman78] use global information of the graph. The betweenness centrality is based on the frequency at which a node is between pairs of other nodes on their shortest paths. In other words, betweenness centrality is a measure of how often a node is a bridge between other nodes. The closeness centrality of a node is the inverse of the sum of distances to all other nodes of the graph.

The importance of a node in a graph can also be characterized by the clustering coefficient [Hansen20] also known as a high density of triangles. The clustering coefficient measures to what extent the neighbors of a node are connected to each other. So, if the neighbors of the node i are all connected to each other, then the node i has a high clustering coefficient.

However, to be able to analyze a graph that could be complex and strongly connected, it is necessary to use visualization tools which, by highlighting these topological properties in the graph, make it possible to visually locate the key nodes of the graph. We therefore discuss, in section 3, related work in graph drawing that make it possible to highlight centrality measures of the nodes in a graph.

3 CENTRALITY VISUALIZATION

Many works in graph drawing made it possible to convey relational information such as centrality measures and clustering coefficient. So, Brandes et al. [Brandes03] and Brandes and Pich [Brandes11] proposed radial layouts that make it possible to highlight the betweenness and the closeness centralities of the nodes in a graph (see Fig.1). In these methods, each node is constrained to lie on a circle according to its centrality value. Therefore, nodes with a high centrality value are close to the center and those of low value are on the periphery.

Dwyer et al. [Dwyer06] also proposed 3D parallel coordinates, orbit-based and hierarchy-based methods to simultaneously compare five centrality measures (degree, eccentricity, eigenvector, closeness, betweenness). The difference between these three methods is how centrality values are mapped to the nodes position. Therefore, for 3D parallel coordinates the nodes are placed on vertical lines; for orbit-based the nodes are placed on concentric circles and for hierarchy-based the nodes are placed on horizontal lines. On the other hand, Raj and Whitaker [Raj17] proposed an anisotropic radial layout that makes it possible to highlight the betweenness centrality of the nodes in a graph. In this method, they proposed to use closed curves instead of concentric circles, arguing that the use of closed curves offers more flexibility to preserve the graph structure, compared to previous radial methods.

However, it would be difficult to visually identify some nodes that have the same centrality value, compared to the radial layouts. The proposed methods of Dwyer et al. [Dwyer06] make it possible to compare many centrality measures, but it would be difficult to identify the central nodes, compared to that of Brandes and Pich [Brandes11]. On the other hand, 2D methods suffer from lack of display space when one needs to display a large graph in terms of number of nodes and edges.

Kobina et al. [Kobina20] then proposed 3D extensions of the radial layouts of Brandes and Pich in order to better handle the visualization of complex and large graphs (see Fig.2). Their methods consist in projecting 2D graph layouts on 3D surfaces. These methods reduce node and edge overlap and improve the perception of the nodes connectivity, compared to the 2D radial layouts. However, some nodes and edges are less visible depending on the projection surface and edge drawing method. Indeed, the use of straight edges caused most of them to be inside the half-sphere and others to cross the half-sphere. Furthermore, most of the edges are on the surface for the conical projection and outside the surface for the toric projection. Some nodes and edges are then less visible. Therefore, it increases the cognitive effort of an observer. Last, this method has not been evaluated.

However, the solution of Kobina et al. seems the most promising one, so we propose to improve it to overcome its limitations and then to formally evaluate it.

4 IMPROVEMENTS OF THE 3D RADIAL LAYOUTS

In order to reduce node and edge overlap and the cognitive effort in the proposed methods of Kobina et al.

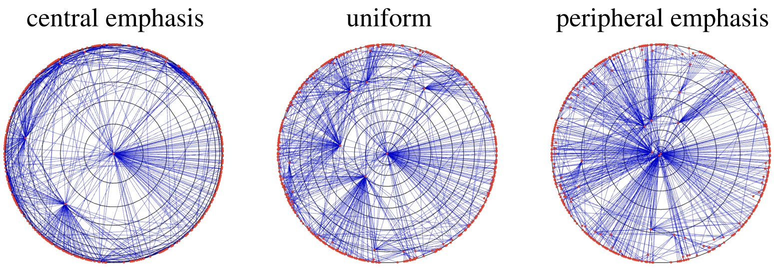


Figure 1: Betweenness centrality: 2D radial visualization of a graph (419 nodes and 695 edges). Center and periphery are emphasized using transformed radii $r'_i = 1-(1-r_i)^3$ and $r'_i = r_i^3$ $(0 \leq r_i \leq 1$ and $0 \leq r'_i \leq 1)$, respectively [Brandes11].

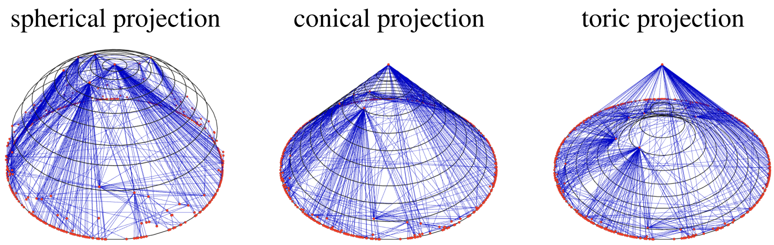


Figure 2: Betweenness centrality: uniform 3D radial visualization of a graph (419 nodes and 695 edges). The spherical projection spreads out more the peripheral nodes than the central nodes while the toric projection spreads out more the central nodes than the peripheral nodes. The conical projection evenly distributes nodes.

[Kobina20] (Fig.2), we projected the edges onto the visualization surfaces.

Let e be an edge to be projected onto a visualization surface and that connects the nodes j and k, and P_i be any point belonging to e.

$P_i = P_j + (P_k - P_j)t$ where P_j and P_k are respectively the position of the nodes j and k, and $t = i/(n-1)$ where n is the number of control points of the edge e and $i \in \{0, 1, ..., n-1\}$.

4.1 Edge projection onto the cone

In this section, we describe the various steps that are relevant to the proposed method of projecting edges onto the cone:

- we compute the angle θ between the x axis and the z axis of the point to be projected: $\theta = \frac{180}{\pi} atan2(z_{P_i}, x_{P_i})$
- we then rotate by θ about y axis. Let R be the rotation result:
$$R = \begin{bmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$
- we compute the projected point P_p
$P_p = \frac{x_{P_i} x_R + y_{P_i} y_R + z_{P_i} z_R}{||R||} \cdot R$
- we finally compute the altitude $y_{P_p} = 1 - \sqrt{x_{P_p}^2 + z_{P_p}^2}$

4.2 Edge projection onto the half-sphere

Here we describe the projection method of the edges onto the half-sphere:

- we compute the projected point $P_p = \frac{P_i}{||P_i||}$
- we then compute the altitude $y_{P_p} = \sqrt{1 - (x_{P_p}^2 + z_{P_p}^2)}$

4.3 Edge projection onto the torus portion

In this section, we describe the projection method of the edges onto the torus portion in four steps:

- we compute the angle θ between the x axis and the z axis of P_i, the point to be projected: $\theta = \frac{180}{\pi} atan2(z_{P_i}, x_{P_i})$
- we then rotate by θ about y axis. Let R be the rotation result:
$$R = \begin{bmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$
- we compute the projected point $P_p = \frac{P_i}{||P_i||} + R$
- we finally compute the altitude of the point: $y_{P_p} = 1 - \sqrt{1-((r-1)(r-1))}$, with $r = \sqrt{x_{P_p}^2 + z_{P_p}^2}$.

Fig. 3 illustrates the result of our projected edges, compared to that of straight edges used in the proposed methods of Kobina et al. [Kobina20] (see Fig.2).

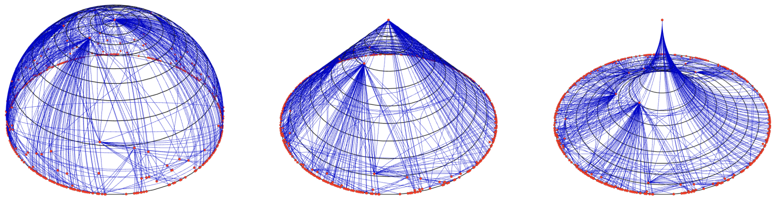


Figure 3: Betweenness centrality: uniform 3D radial visualization of a graph (419 nodes and 695 edges). Edges are projected onto the visualization surfaces, compared to straight edges observed in the proposed methods of Kobina et al. [Kobina20] (see Fig.2).

Therefore, by projecting the edges onto the visualization surfaces, we improved the readability of the graph. Furthermore, there are no edges that cross the visualization surface.

5 EVALUATION

We conducted a human-centered evaluation through a series of tasks performed on generated graphs in order to compare the efficiency score and the time to complete a task of the 3D layouts with projected edges (Fig.3) to those of the 2D radial layouts. We used these 2 metrics to determine whether a kind of visualization performs better or worse than the others with respect to a task. We specifically wanted to answer the following research questions:

Comprehension. What are the effects on comprehension by projecting 2D radial layouts on 3D surfaces?

User Experience. What are the perceived effects of 2D and 3D graph layouts?

5.1 Tasks

Kobina et al. [Kobina20] suggested that the projections of the uniform 2D representation highlight either the center, the periphery, or either moderately the center and the periphery. So we chose these three following tasks that are related to the central nodes, to the peripheral nodes and to the dense areas of a graph:

- **Task 1 (related to the central nodes).** The participants were asked to find one of the nodes that has the greatest degree among the most central node's neighbors.
- **Task 2 (related to the peripheral nodes).** The participants were asked to find one of the least central nodes that has at least two neighbors.
- **Task 3 (related to the dense areas of a graph).** The participants were asked to find one of the nodes of degree at least 3 that has the highest clustering coefficient except 100%.

5.2 Hypothesis

We made hypotheses based on efficiency and speed.

Efficiency: We expected that 3D layouts would perform significantly better in efficiency score than 2D layouts. With respect to task 1, we expected that the participants would score poorly on the 2D that emphasizes the periphery than on the other visualization surfaces. We therefore made the following hypotheses:

H1. The 2D that emphasizes the periphery will perform worse than other layouts when one is interested in the central nodes.

H2. Unlike 2D visualization that emphasizes the periphery, 3D projections that naturally emphasize the periphery (cone and half-sphere) will not be less efficient to perform tasks related to the center.

Then, regarding task 2 we expected that the participants would have bad efficiency score on the 2D that emphasizes the center than on the other surfaces. Moreover, Kobina et al. [Kobina20] suggested that combining the central emphasis with the 3D projections reduces the crushing of the peripheral nodes. So, we made the following hypotheses:

H3. The 2D that emphasizes the center will perform worse than other layouts when tasks are related to the periphery.

H4. Unlike 2D visualization that emphasizes the center, 3D projections that naturally emphasize the center (cone and torus portion) will not be less efficient to perform tasks related to the periphery.

As far as the dense areas (task 3) are concerned, we expected that the participants would perform significantly better on the 3D surfaces than on the 2D layouts. We then made the following hypothesis:

H5. 3D layouts will be better suited for exploring the dense areas of a graph than 2D layouts.

Speed: Whatever the task, we expected that 3D layouts would perform significantly better in speed than 2D layouts. We therefore made the following hypothesis:

H6. The time to complete a task will be longer with 2D layouts than with 3D ones.

5.3 Experimental protocol and measures

We conducted an experimental study using a WebGL version of our graph visualization system because of the Covid-19. Here are links to our experiment for a given configuration starting from 2D `https://anonymnam.github.io/radialvig3dxp1` and for another given configuration starting from 3D `https://anonymnam.github.io/radialvig3dxp2`. The participants could therefore perform the experiment remotely on their own laptop. Kobina et al. [Kobina20] suggested that the combination of the uniform 2D representation and the different projections makes it possible to obtain in addition an emphasis on the center or on the periphery. So in this study, our goal is to show that these 3D methods could be better suited to explore and to analyze graphs whatever the interest (the central or peripheral nodes, the dense areas), compared to the 2D representations. Indeed, since Kobina et al. [Kobina20] optimized the spatial distribution of the nodes and since we projected the edges onto the surfaces, there could be more accurate responses to different tasks. Additionally, the exploration of a graph would be easier, because thanks to these improvements one could better perceive the nodes connectivity. Furthermore, we wanted to analyze the usability of the 3D for exploring and analyzing graphs. On the other hand, we wanted to identify the best layout that could be used to visualize large graphs.

For our experiment we chose to use the betweenness centrality. However, the results of our assessment are not affected by the type of centrality measure used. It will therefore be enough to assess the interest of the proposed methods. We first generated, with the Stochastic Block Model algorithm [Holland83, Stanley19, Lee19], 6 different graphs (250 nodes and 855 edges) that have equivalent topological characteristics ($density = 0.027$ and $diameter = 8$), since it is difficult to find in databases several graphs of the same size with these equivalent topological characteristics. The density of a graph represents the ratio between the number of existing edges and the maximum number of possible edges, while the diameter is the maximum distance between any pair of nodes.

The Stochastic Block Model is a generative model for random graphs which usually produces graphs containing community structure. This means that each node has a fixed community membership, which determines with which probability an edge exists to other nodes [Snijders97]. The model is defined by the number of nodes n, the number of communities C, a probability vector $\alpha = (\alpha_1, ..., \alpha_C)$ specifying the distribution of the nodes on the communities and a symmetric matrix $M \in \mathbb{R}^{CxC}$ with entries in $[0,1]$ specifying the connectivity probabilities [Holland83]. Therefore, the obtained graphs have similar topological characteristics, while being sufficiently different to avoid a learning effect when switching from one to another.

We then built 24 configurations with the various surfaces so that each surface and graph is performed at least once as first, using something similar to the concept of the Latin square [Freeman79, Richardson18]. A Latin square is an n x n array filled with n different symbols in such a way that each symbol occurs exactly once in each row and exactly once in each column. For our configurations, we respected a distribution order between 2D and 3D surfaces so that the running order of a 2D representation corresponds to the one of its equivalent 3D surface. For example, if a configuration starts with the 2D surfaces and the first surface is the one that emphasizes the center, then the first 3D surface will be the torus portion, since it is the one to highlight the most the center. So we make sure that each configuration is tested as many times before as after each of the other configurations. Additionally, half of the participants started the experiment with the 2D followed by the 3D and the second half of the participants with the other way around.

During the experiment and for each task and each surface, we measure an efficiency score and the time spent to complete a task. As the experiment is done remotely, the participants' performance is automatically saved when they validate their responses. Below is how we compute the efficiency score of the participants.

Task 1. Find one of the Nodes that has the Greatest Degree among the most Central Node's Neighbors.

$$score_i = \begin{cases} 100 * (deg_i / deg_{ideal}), & \text{if } d(ctr,i) = 1 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where deg_i is the degree of the selected $node_i$. deg_{ideal} is the greatest degree among the central node's neighbors and $d(ctr,i)$ is the shortest distance between the central node and $node_i$. Thus, $node_i$ must be directly connected to the central node, i.e. $d(ctr,i)$ must be equal to 1.

Task 2. Find one of the least Central Nodes that has at least two neighbors.

$$score_i = \begin{cases} 100 * (1 - c_i)/(1 - c_{ideal}), & \text{if } c_{ideal} \neq 1 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where c_i and c_{ideal} are respectively the centrality value of the $node_i$ and that of the ideal node. Furthermore, the score is 0 if the degree of the selected node is less than 2. Indeed, it is easy to check that the degree of the selected node is at least 2. Thus, the score is 0 if the condition is not met. Otherwise, the score varies from 0 at the center to 1 for a node of degree at least 2 and the most on the periphery.

Task 3. Find one of the Nodes of Degree at least 3 that has the Highest Clustering Coefficient except 100%.

$$score_i = \begin{cases} 100 * (ccf_i - ccf_{worst})/k, & \text{if } k > 0 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where $k = (ccf_{ideal} - ccf_{worst})$. ccf_i, ccf_{worst} and ccf_{ideal} are respectively the clustering coefficient of the $node_i$, the worst clustering coefficient and the highest clustering coefficient except 100%. The score is therefore 0 if the degree of the selected node is less than 3 or if the clustering coefficient of the selected node is 100%. Otherwise, we compute the score using equation 3.

Since our experiment is done remotely, we organized a video conference for each participant in order to supervise the experiment's process. The experiment consists of a training phase and an evaluation phase. Before starting the training phase, the participants are instructed about the experiment procedure, its environment, navigation and interaction techniques. For example, when the mouse hovers a node, a tooltip shows its clustering coefficient value and its degree. On the other hand, when the participants select a node, its neighbors are highlighted. They are also given the essential notions about graphs in order to ensure that they have the useful knowledge for the experiment. In the training phase, the participants are asked to perform the above tasks on a small graph (the karate club's graph [Zachary77]) and on each surface. Once familiar with the system, they move on to the evaluation phase, but with generated graphs. If the participants are ready to start the training or the evaluation, they click on a start button to see the first task to complete and the next task is automatically displayed after validating the previous task response. At the end of the experiment, the participants complete questionnaires related to the system usability (SUS) [Brooke96] and the user experience.

5.4 Participants

We needed a number of participants that would be a multiple of 24 in order to encounter the same number of these 24 configurations mentioned above. Thus, there were 24 participants (9 female, 15 male) and they were recruited among our colleagues in the laboratory and among students: 50% were between 18 and 25 years old, 37.5% were between 25 and 35, and 12.5% were more than 35 years old. Moreover, most participants had no experience in data analysis and data visualization, but some of them had gaming experience.

6 RESULTS

6.1 User performance

We present here the main results from the analysis of the data collected during our experiment through nonparametric tests using the Kruskal-Wallis and post-hoc tests using the Dunn's method [Dunn64, Sangseok18]. We used nonparametric tests since none of the samples comes from a normal distribution (normality tests were done using the Shapiro-Wilk test). As a reminder, the variables analyzed are the efficiency score and the time for each task and each surface. All data were statistically analyzed using the statistics sub-package of **SciPy** and the **scikit-posthocs** package.

6.1.1 Efficiency score

Task 1: Find one of the Nodes that has the Greatest Degree among the most Central Node's Neighbors.

The nonparametric test showed that there is a statistically significant difference between the visualization surfaces and cannot be due to chance ($statistic = 31.45, p = 10^{-5} < 0.05$). Moreover, the post-hoc test (see table 1) showed that the 2D that emphasizes the periphery had a difference of means. So, we validate hypothesis H1 that the 2D layout that emphasizes the periphery performs worse than other layouts when tasks are related to the central nodes. Furthermore, we validate hypothesis H2 that the 3D projections that naturally emphasize the periphery are not less efficient for performing center-related tasks.

Task 2: Find one of the least Central Nodes that has at least two neighbors.

There is a difference that is statistically significant between the 2D that emphasizes the center and all the other surfaces (see table 2), because the test statistic is 40.31 and the corresponding p-value is $10^{-5} < 0.05$. Thus, we validate hypothesis H3 that the 2D layout that emphasizes the center performs worse than other layouts when a task is related to the peripheral nodes. Moreover, we validate hypothesis H4 that the 3D projections that naturally emphasize the center are not less efficient to perform tasks related to the periphery.

Task 3: Find one of the Nodes of Degree at least 3 that has the Highest Clustering Coefficient except 100%.

The difference between the various surfaces is not statistically significant, since the test statistic is 6.0 and the corresponding p-value is $0.31 > 0.05$. We therefore reject hypothesis H5 that 3D layouts are better suited for exploring the dense areas of a graph than 2D layouts. However, the difference in means (see Fig.4) could lead us to say that the 2D that emphasizes the center performs better than other layouts when tasks are related to the dense areas of the graph, but the statistic analysis failed to demonstrate it.

Based on the efficiency score analysis, the 3D surfaces are well suited for carrying out tasks that are related to the central or the peripheral nodes, since we validated hypotheses H1, H2, H3 and H4. However, we rejected hypothesis H5.

	2D central	2D peripheral	2D uniform	Cone	Half sphere	Torus
2D central	1	10^{-4}***	0.37	0.68	0.42	0.40
2D peripheral	10^{-4}***	1	10^{-3}***	10^{-4}***	10^{-3}***	10^{-3}***
2D uniform	0.37	10^{-3}***	1	0.64	0.93	0.96
Cone	0.68	10^{-4}***	0.64	1	0.70	0.67
Half sphere	0.42	10^{-3}***	0.93	0.70	1	0.97
Torus	0.40	10^{-3}***	0.96	0.67	0.97	1

Table 1: Efficiency score: Task 1: P-values of the post-hoc test using Dunn's method (significant p-values starred (*$p < 0.05$, **$p < 0.01$, ***$p \leq 0.001$)).

	2D central	2D peripheral	2D uniform	Cone	Half sphere	Torus
2D central	1	10^{-5}***	10^{-2}**	10^{-4}***	10^{-5}***	10^{-3}***
2D peripheral	10^{-5}***	1	0.16	0.69	0.71	0.22
2D uniform	10^{-2}**	0.16	1	0.31	0.08	0.86
Cone	10^{-4}***	0.69	0.31	1	0.44	0.41
Half sphere	10^{-5}***	0.71	0.08	0.44	1	0.11
Torus	10^{-3}***	0.22	0.86	0.41	0.11	1

Table 2: Efficiency score: Task 2: P-values of the post-hoc test using Dunn's method (significant p-values starred (*$p < 0.05$, **$p < 0.01$, ***$p \leq 0.001$)).

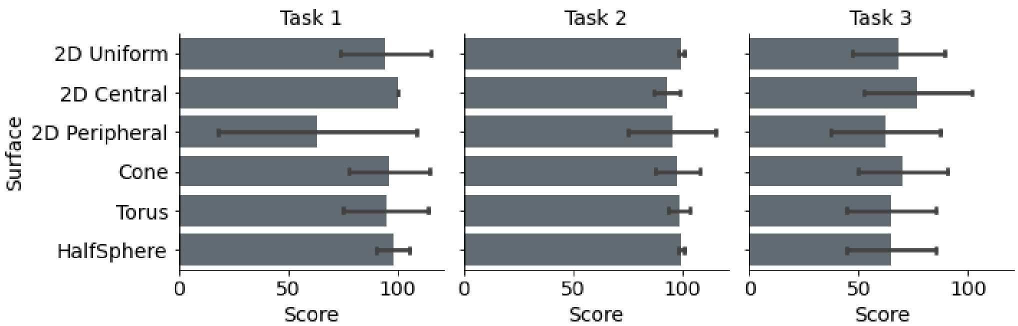


Figure 4: Efficiency score: Means and standard deviations of the efficiency score by task and by visualization surface.

6.1.2 Time

Task 1: Find one of the Nodes that has the Greatest Degree among the most Central Node's Neighbors.

From Fig.5, we could say that the participants spent more time on the 2D that emphasizes the periphery, compared to all other visualization surfaces. However, there is no difference that is statistically significant between the various surfaces ($statistic = 5.990, p = 0.31 > 0.05$). We therefore reject hypothesis H6 that the time to complete a task is longer with 2D layouts than with 3D ones.

Task 2: Find one of the least Central Nodes that has at least two neighbors.

There is no difference that is statistically significant between all the surfaces ($statistic = 1.65, p = 0.90 > 0.05$). We therefore reject hypothesis H6.

Task 3: Find one of the Nodes of Degree at least 3 and that has the Highest Clustering Coefficient except 100%.

We reject hypothesis H6, since the test statistic is 1.04 and the corresponding p-value is $0.96 > 0.05$.

With regard to the time analysis, hypothesis H6 is rejected, since the difference is not statistically significant between the various layouts.

6.2 User experience

As mentioned above (in section 5.3), at the end of the experiment, the participants were asked to complete a questionnaire related to the system usability and to their experience. The usability assessment showed that 3D layouts are more usable than 2D ones, with a score of 81.46 against 75.21 (the usability threshold for a system is $70/100$ [Brooke96]). Regarding the participants experience, the participants were asked whether they understood the requested tasks, if they had difficulty interacting with the system, and if they had visual fatigue. The results were that 23 participants over 24 understood the requested tasks, 7 over 24 had difficulty interacting with the system and 7 participants over 24 declared having visual fatigue.

The participants were also asked to specify the surfaces that enabled them to better perform the requested tasks, on the one hand, and to identify the surfaces with which

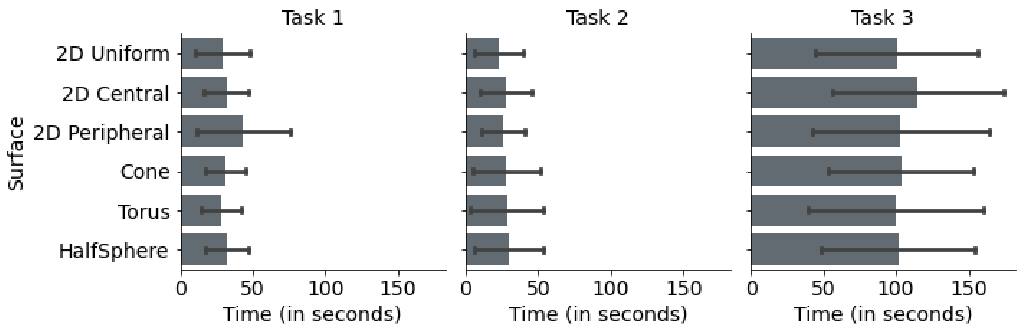


Figure 5: Time: Means and standard deviations of the time by task and by visualization surface.

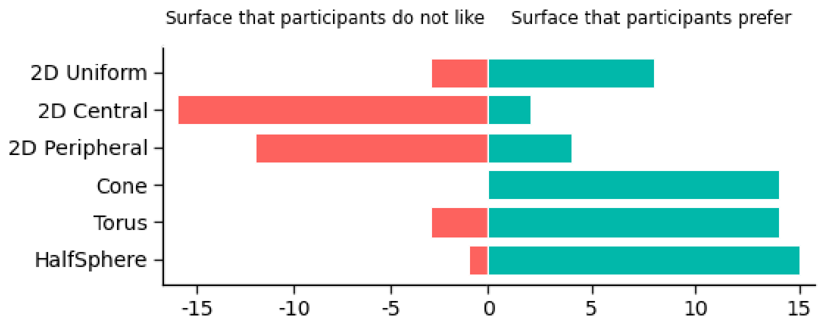


Figure 6: Distribution of user preferences for liking (in green) and disliking (in red) visualization surfaces.

they had difficulty completing the requested tasks, on the other hand. Based on their feedback, 3D surfaces have significantly contributed to the successful completion of the various tasks, compared to the 2D representations (uniform 2D, the 2D that emphasizes the center or the periphery). Fig.6 illustrates the distribution of user preferences for liking and disliking visualization surfaces. It shows that the participants significantly prefer 3D layouts when performing tasks. Moreover, the 2D that emphasizes the center and the one that emphasizes the periphery alone total 80% of the dislike votes while the cone makes 0% dislike.

7 DISCUSSION

Some nodes would be less visible with the use of the straight edges in the proposed methods of Kobina et al. [Kobina20]. Indeed, combining the peripheral emphasis and the projection of the nodes and edges on the half-sphere or on the torus portion, some intermediate nodes would be less visible due to the type of surface, unlike the conical projection. Furthermore, with uniform projections, some nodes and edges would be less visible in the dense areas according to the projection surface. Thus, projecting the edges onto the visualization surface, we reduced the overlap of the nodes and the edges, and we therefore improved the overall readability of the graph.

As far as our evaluation is concerned, we expected that each 3D visualization could be the best for one of the tasks, hence the interest of switching from one type of projection to another depending on the task to be carried out. However, we validated hypotheses H1, H2, H3, H4, since the statistic test results showed that there are differences in efficiency score when tasks are related to the central and peripheral nodes.

Indeed, these results made it possible to validate hypotheses H1 that the 2D that emphasizes the periphery is the worst of the surfaces to visualize the center, and H3 that the 2D that emphasizes the center is the worst of the surfaces to visualize the periphery with respect to the efficiency score of tasks 1 and 2. Moreover, we validated hypotheses: 1) H2 that 3D projections that naturally emphasize the periphery (cone and half-sphere) are not less efficient to perform tasks related to the center; 2) H4 that 3D projections that naturally emphasize the center (cone and torus portion) are not less efficient to perform tasks related to the periphery, always regarding the efficiency score of tasks 1 and 2.

On the other hand, we rejected hypotheses H5, since we were not able to prove that 3D layouts are better suited to explore the dense areas of a graph than 2D layouts. We also rejected hypothesis H6 that the time to complete a task is longer with 2D layouts than with 3D ones, because there is no difference that is statistically significant. We could therefore say that the 2D versus 3D debate still persists [Cliquet17]. However, the participants' feedback showed that the 3D surfaces could be well suited for completing the various requested tasks successfully, compared to the 2D surfaces. Moreover, the system usability assessment showed that 3D is above 2D, since its score is 81.46 and the one of 2D is 75.21.

Table 3 summarizes which hypotheses have been validated (✓) or rejected (✗) for which task and for which measure.

Metrics	Efficiency					Speed
Hypotheses	H1	H2	H3	H4	H5	H6
Task 1	✓	✓				✗
Task 2			✓	✓		✗
Task 3					✗	✗

Table 3: Summary of evaluation hypotheses.

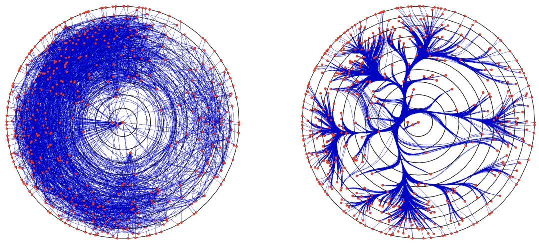
8 CONCLUSION

Our improvements of the edge drawing for 3D radial layouts lead to a better usability of these layouts. These improvements consisted in projecting the edges onto each visualization surface in order to reduce the node and edge overlap. The human-centered evaluation we conducted showed that these 3D layouts can be more efficient than 2D layouts for tasks that are related to the central and peripheral nodes, even if we were not able to say that the time to complete a task is shorter with 3D layouts than with 2D layouts. Additionally, the participants significantly preferred 3D layouts, because they had a better feeling on the 3D when carrying out the requested tasks, compared to 2D layouts. Thus, adding a third dimension to the 2D radial layouts improves the user experience.

9 FUTURE WORK

In the future, we will also study in detail the results obtained with large graphs in order to check whether current trends are confirmed. Specifically, we will check if 3D would perform better than 2D on a 75-inch 4K screen and if immersive 3D would perform better than 3D on a 75-inch 4K screen. We are already conducting a human-centered evaluation with large graphs using a 75-inch 4K screen and in virtual reality. Moreover, we projected the 2D views on other types of 3D surfaces (a parabola, a Gaussian, a hyperboloid and a square root). Thus, we will study in more details the results of these contributions in order to identify the most appropriate approach or combination of approaches that could be used to visualize large and complex graphs.

Furthermore, when a graph contains several thousands of edges, the visualization often suffers from clutter (see the left image of Fig.7). The graph can therefore be almost impossible to analyze. Thus, in order to declutter graphs in the proposed methods of Kobina et al. [Kobina20] and highlight the connectivity between groups of nodes, we will exploit the computer graphics acceleration techniques and the kernel density estimation edge bundling algorithm [Hurter2012]. Fig.7 illustrates the result of a graph which was generated using Stochastic Block Model algorithm presented in section 5.3. It is thus possible to see how groups of nodes are connected to each other with a bundled graph. However, we lose the detailed connectivity of a node (for instance, edges between a node and its neighbors). It could therefore be useful to combine the bundled and the unbundled edges for further analysis if one would need to switch between detailed and bundled views.



(a) (b)

Figure 7: Top view from the cone of a generated graph (500 nodes and 3294 edges): (a) unbundled and (b) bundled using KDEEB algorithm proposed by Hurter et al. [Hurter2012]. Edge bundling makes it possible to declutter the graph.

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