Aesthetic-Driven Navigation for Node-Link Diagrams in VR

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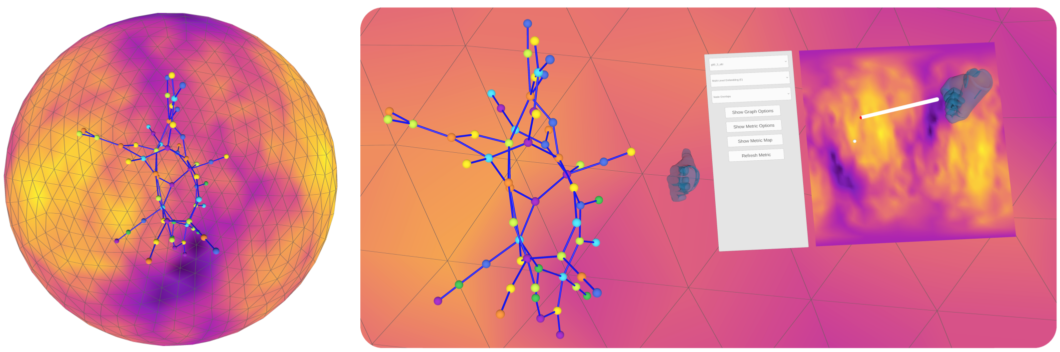

Figure 1: Our VR system visualizes quantitative aesthetic measures for each perspective on a 3D node-link diagram using color (here: yellow corresponds to optimal viewports regarding the selected measure, purple areas visualize adverse perspectives). An icosphere surrounding the user (left) and a 2D map (right) present the viewport quality and can be used for spatial navigation.

ABSTRACT

Visual network exploration is essential in numerous disciplines, including biology, digital humanities, and cyber security. Prior research has shown that immersive, stereoscopic 3D can enhance spatial comprehension and accuracy in exploring node-link diagrams. However, 3D graphs can present challenges, including node occlusion and edge crossings, which necessitate continual manual perspective adjustments. We introduce a virtual reality (VR) framework that assists users in navigating to optimal viewing points based on their current task, addressing these issues. The framework quantifies the perceptual quality of viewports based on graph drawing aesthetics suggested by the literature. This information is then visualized in two ways: on a spherical 3D representation surrounding the user and on a handheld 2D overview map. Users can interact with both representations to easily adjust their viewpoint. Moreover, they can interactively combine different aesthetics to discover the optimal viewing points for their specific tasks. Two qualitative evaluations involving law enforcement and biology experts demonstrate the value of our approach. Domain experts reported that the suggested viewports corresponded to their intuition and simplified the process of finding task-supportive perspectives with minimal interaction. Our approach can be incorporated into existing VR graph exploration tools, improving the initial perspective selection and reducing manual navigation.

CCS CONCEPTS

• **Human-centered computing → Virtual reality**; **Visualization design and evaluation methods**; **Graph drawings**.

KEYWORDS

Viewport optimization, network exploration, node-link diagrams, 3D navigation, graph aesthetics, virtual reality

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1 INTRODUCTION

Network data occurs in many domains, such as biology [3], psychology [10], infrastructure [71], and crime investigation [22].Measures like centrality, cluster coefficient, closure, and others help to assess and compare networks numerically, but the visual exploration still proves highly valuable [55, 72]. The visual exploration mainly relies on matrix representations that scale well with increasing network complexity and node-link diagrams that are often better at reflecting the topology [26].

Over the last decades, the research field immersive analytics (IA) emerged, employing new display and visualization technology like virtual reality (VR) and augmented reality (AR) together with multimodal interaction to overcome the limitations of 2D-based mouse and keyboard visual analytics applications. IA strives to remove barriers between researchers and their data, supporting collaborative work and natural experiences to increase the user's understanding, engagement, and immersiveness [12, 49]. Consequently, IA has also been applied to enhance the visual exploration of networks. Several studies found immersive stereoscopic 3D (S3D) approaches to significantly improve multiple aspects of the exploration workflow of node-link diagrams [7, 27, 28, 77–79]. Node-link representations can be naturally extended to 3D since neither positions nor form factors of nodes or edges rely on 2D spaces. Matrix representations have no natural 3D counterpart making them less promising for three-dimensional environments [40]. Therefore, our work focuses on node-link representations in an immersive setup.

Despite the advantages shown in previous work, there are also new challenges introduced by incorporating IA. These challenges target the visualization of graphs in 3D and how the extended design space can be incorporated, but also the interaction with the data. In particular, navigation becomes a central interaction technique for 3D graphs since the third dimension introduces undesired visual artifacts, such as edge crossings or node occlusions, requiring perspective changes. Layout algorithms for 3D node-link diagrams intend to reduce these artifacts by optimizing graph properties like energetic stress, edge crossings, edge lengths, and others [23]. While few approaches consider node-link representations surrounding observers [44], for the scope of this work, we focus on layouts perceived by an external user. Overview-oriented representations, as opposed to inside views, are more prevalent and often advantageous [43]. Despite significant advances in quality, modern layout algorithms can not entirely prevent certain areas from being denser than others, nor can they entirely eliminate overlaps (e.g., due to consideration of competing positioning metrics). This necessitates the careful choice of perspective in a 3D setup, as it can make a significant difference from which side and angle viewers observe a graph representation. Most often, there is no universal, optimal perspective, and instead, the adequacy of a viewport is highly task-dependent [8]. Thus, immersive graph exploration tools require frequent, manual interactions to change the perspective until a viewport supporting the current visual exploration task sufficiently is found. This can be achieved by moving within the virtual environment, which often necessitates physical movement, or by manipulating the visual representation (e.g., through rotation). Identifying and selecting suitable viewports for varying tasks in the sense-making process can be challenging and time-consuming. To tackle this issue, we present a framework facilitating the spatial navigation for node-link diagrams in VR based on task-specific, quantitative graph aesthetic measures. Thereby, we make the following contributions:

- We develop a technique to quantify the quality of different perspectives on a 3D graph based on graph aesthetics.
- We present a VR system implementing two visualizations showing the task-specific viewport quality and allowing for guided spatial navigation.
- We report on two expert evaluations showing the value of our approach for the work of researchers in different domains, thereby highlighting the potential for existing immersive network exploration frameworks.

2 RELATED WORK

Related concepts to our work are graph navigation in AR and VR, the optimization of viewports in general and for graphs in particular, and graph drawing aesthetics with corresponding user studies.

2.1 Graph Navigation in AR/VR

Several navigation techniques for perspective changes in AR and VR have been proposed. The mobility provided by head-mounted displays (HMD) is often used for *free walking* within the physical space leading to direct viewport changes in the virtual space [17, 30, 42], while other approaches use a *free fly camera* [11, 68]. Erra et al. [21] translate hand gestures into camera movements. Instead of employing direct camera movement, some systems incorporate *teleportation*, where target camera positions are defined [16, 68]. Drogemuller et al. [16] present the *Worlds-in-Miniature* concept involving an interactive miniature version of the original virtual environment. Similarly, Sorger et al. [68] use the selection of a node to initiate a camera flight leading to a beneficial camera perspective for observing the selected node. Instead of moving the camera, multiple approaches apply rotation or translation to change the perspective. Belcher et al. [7] incorporate a physical plate coupled to an AR graph allowing changes to the graph representation by manipulating a real-world object. For VR systems, multiple applications use physical controllers [56, 68] or gestures [36] to invoke graph rotations. More directly, controllers or tracked hands can be used to *grab* and naturally rotate or move a graph representation [38, 66].

Viewport changes in AR and VR graph applications are mainly based on manual manipulations of the graph visualization or the camera. The few attempts to automatically choose beneficial viewports are very limited. Our work addresses this gap by providing automated navigation based on multiple viewport quality criteria.

2.2 Viewport Optimization

Optimizing the viewport for 3D visualizations can reduce occlusion and increase the quantity of visible information. In addition to manual adjustments, researchers have explored automated viewport assessment and modifications. Various measures have been proposed for general 3D representations. Toussaint et al. define a "nice viewport" for a 3D object as a projective view showing relevant features clearly [70]. Other definitions involve the number of visible pixels [4], the number of visible faces [57], the Shannon Entropy measuring perceivable information [74], the Kullback-Leibler divergence comparing projected areas and 3D object shapes [67], and depth maps for tessellation-independent viewport assessment [73]. The applicability of these metrics highly depends on the use case [24].

Besides general 3D models, viewport quality measures were proposed for molecule visualization [15, 75, 76], composition of objects in 3D scenes [50, 57], and visualization of 3D cadastral systems [51].

Some approaches target the unique characteristics of graph structures. Eades et al. [20] and Houle et al. [31] propose methods for finding optimal 2D orthographic projections of 3D graphs by minimizing occlusions of edges and vertices. Friedrich et al. [25] define criteria (e.g., absence of temporary edge crossings) for transitions between graph layouts preserving the user's mental map. Ahmed et al. [1] generate camera paths for 3D graphs, optimizing the information in the user's viewport while maintaining the mental map. They also present navigation techniques for graphs using criteria for mental-map-preserving transitions [2] similar to those of Friedrich et al. [25]. Elsid et al. [53, 54] investigate viewpoints optimizing node-node and edge-edge occlusion for 3D force-directed graphs.

Multiple measures for viewport quality were proposed and applied to different applications. While most approaches focus on non-graph-specific visual properties, a few methods targeting node-link diagrams concentrate on overlaps and consider only a single, optimal viewport, disregarding the specific task. In contrast to these methods, we consider multiple measures of viewport quality for 3D node-link diagrams, along with task-specific combinations. Further, we calculate and visualize the quality of all possible perspectives.

2.3 Graph Drawing Aesthetics

Graph drawing algorithms minimize negative effects, such as edge crossings, while maximizing desirable properties like symmetry [23]. Layout algorithms evolved over many decades, but research on the perceptual effects of graph drawing aesthetics is more recent.

Purchase et al. [62] explore the perceptual effects of various graph aesthetics for topological tasks, finding significance in *edge crossings*, *bends*, and *symmetry*. Later, Purchase et al. [59] report on the impact of aesthetics on accuracy and answer time, finding *edge crossings* to be the most effective one, followed by *edge bends* and *symmetry* while maximizing *orthogonality* and *angular resolution* (i.e., the angle between edges originating from a common node) reveal no effect. In another study [64], the authors validate that *edge crossings* is the most effective graph drawing aesthetic and find *orthogonality* to be of relevance too. Kobourov et al. [41] report on the effect of *edge crossings*, finding it strongly observable for small graphs but less relevant for larger graphs. Ware et al. [80] determine *edge crossings* and the *continuation* of multi-edges (no large direction changes on paths) to be essential factors for shortest path tasks. They also find the *length of the shortest path* and the *number of branches* emanating from nodes contained in the shortest path to be of high relevance, which was confirmed by Huang et al. [32]. Further, Huang et al. [33, 34] investigate *crossing angles* between edges finding a significant impact on answer time and accuracy for path tracing tasks and suggesting 70° as the optimum for crossing angles. They further report on the effects of three measures for the *angular resolution*, finding all of them to be significant [35]. Baum [6] assesses literature-suggested aesthetics and confirms their effects with a study using *repertory grids*. Using curved edges to improve angular resolution could not compete with straight edges [63, 81]. Further aesthetics were proposed without evaluation, such as minimizing the drawing *area* [5, 61, 69], *node overlaps* [18, 48], the *sum of edge lengths* [5, 69], the *maximal edge length* [5, 69], and avoiding high *variances across edge lengths* [5]. Some approaches transform abstract aesthetics to continuous, bounded functions [18, 19, 60].

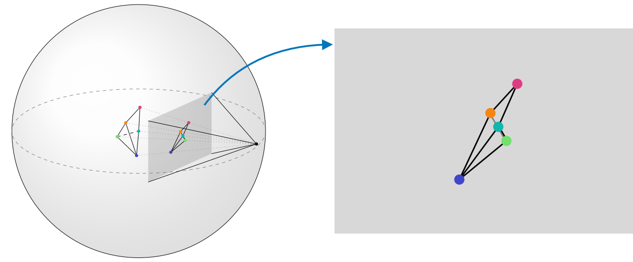

Figure 2: A 3D graph visualization in the center of a sphere (left) is projected to 2D (right) using a perspective projection.

Multiple aesthetics were proposed and proved relevant in various evaluations. The interplay of combined aesthetics and their task-specificity remains under-explored. In our approach, we incorporate eight aesthetics based on the existing literature and investigate combinations of these, targeting four different tasks.

3 AESTHETIC-DRIVEN GRAPH NAVIGATION

Currently, VR systems visualizing node-link diagrams rely on frequent manual viewport changes without guidance. However, incorporating graph aesthetics for automated spatial navigation has the potential to increase the user experience with the system and support network exploration tasks of researchers. In our work, we present a method for calculating the quality of all viewports in a VR environment based on graph drawing aesthetics, incorporating visual representations to display results that can be used to change the viewport interactively, and combining different aesthetics to calculate task-specific viewport quality.

3.1 Viewport Quality Calculation

As previously defined, we consider 3D graph layouts from an observer's perspective, situated outside of the graph. Therefore, the set of all possible viewports can be expressed by the surface points of a sphere surrounding the 3D node-link representation. A vector encoding the direction from a point on the sphere's surface to its center represents one possible user perspective. Despite constant minor movements by a VR user's head, perceivable aesthetic changes—such as whether two nodes overlap—require larger, intentional viewport changes due to the sufficient distance from the node-link representation that allows viewing the entire graph. Thus, instead of a continuous calculation of the infinite number of viewports, we assess the viewport quality for a finite, evenly distributed set of surface points. We achieve this by applying an icosphere as sphere approximation, which comes with the desired property. For one to four subdivisions, the number of vertices are 12, 42, 162, and 642. The number of subdivisions can be freely selected based on the required approximation quality and performance.

Given the finite set of perspectives, we calculate the viewport quality with regard to different graph drawing aesthetics individually for each perspective represented by a surface point. VR vision utilizes two slightly shifted perspective projections, to create a

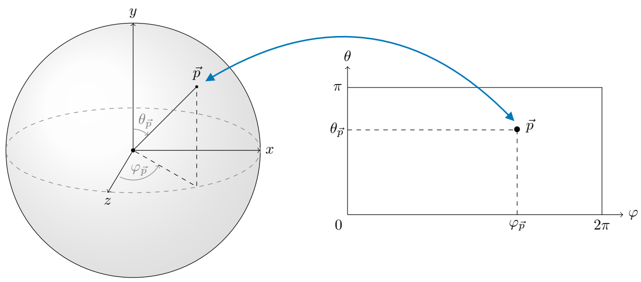

Figure 3: Positions on the sphere surface (left) are projected onto a 2D plane (right) and vice-versa. Using *spherical coordinates*, each 3D point $\vec{p}$ is translated to angles $\varphi_{\vec{p}}$ and $\theta_{\vec{p}}$.

stereoscopic 3D image. Stereoscopy increases the ability to perceive depth and structure in the 3D setup and can impact graph aesthetics like node overlaps, edge crossings, and others: for example, one eye might just see no overlap, while the other already sees a slight overlap. To address the stereoscopic vision of the VR user, one could calculate the projections and aesthetic calculations for both eyes given a fixed perspective and combine the results to one quality measure, for instance, by using the average or maximum value of both views. Given the graph-distance in our setup, these perspective changes are small enough to be negligible, in particular considering the naturally occurring slight head movements. Therefore, we only calculate the projection for the average perspective of both eye, which is equivalent to a stereoscopic projection with an inter-pupil distance of zero, and increases the calculation performance. While image-based approaches could be used to determine the final score for a 2D graph projection, these methods are not accurate and can not detect fully occluded nodes or edges. Hence, we use the internal representation of nodes, project their 3D coordinates into the 2D camera space, and add edges connecting the projected nodes (see Figure 2). In addition to positions, we project the object dimensions depending on distance and perspective, achieving accurate accounting for the viewport-dependent sizes, as required for measures such as node overlap. Given the 2D nodes and edges in an internal representation, all relevant aesthetics measures presented in Section 2.3 and summarized in Table 1 can then be directly calculated. These quality calculations are independent of each other, allowing parallel computations, for instance, using GPU resources.

3.2 Visual Representations

To visualize the results of the viewport quality calculations, we focus on two visual representations: (1) an icosphere surface and (2) a handheld 2D projection pane. These visualizations provide an overview of all perspectives based on a chosen aesthetic measure. This enables observers to evaluate layout algorithm quality (e.g., assessing edge length distribution of all perspectives) and identify optimal viewports based on visual characteristics (e.g., node overlap). In our application, these visual representations also serve as navigation interfaces, enabling direct viewport selection without needing manual camera or graph manipulation.

In the icosphere representation, we directly map quality values to the colors of corresponding vertices and interpolate them using barycentric coordinates (see Figure 1). The quality values are normalized and mapped to a customizable color scale. By default, we use a diverging color map ranging from yellow to purple (best to worst). Although directly displaying quality values at their source tends to be more comprehensible than indirect mappings, it limits visibility (i.e., interesting regions may be positioned behind the user). Thus, we also use a rectangular 2D projection of the three-dimensional icosphere showing all quality values at once. For the mapping, we use a transformation from 3D Euclidean space to the *spherical coordinate system*. Each 3D point can be expressed by an *azimuthal angle* φ, a *polar angle* θ, and the center distance r (see Figure 3). In our case, only points on the sphere surface are converted, making r a constant. Hence, all surface points can be expressed by two angles with finite ranges serving as two dimensions visualized by the pane. Due to the particularities of the coordinate system conversion, sampling in the spherical space would lead to a highly imbalanced distribution of points within the 2D plane. To achieve a rectilinear grid with an even distribution, we use the back-splatting technique, sample in the Euclidean 2D space on the plane, and perform a barycentric interpolation between the triangle vertex values to arrive at the final color value. Associated drawbacks are discussed in Section 6. This approach yields a homogeneous 2D surface representing all quality values (see Figure 4 right).

3.3 Task-Based Viewport Quality

The previous sections describe how we calculate viewport quality based on individual aesthetics and visualize the results for enhanced evaluation and navigation. While optimizing for a particular aesthetic (such as edge crossing) can prove beneficial for specific tasks (as discussed in Section 2.3), it can simultaneously yield unfavorable outcomes concerning other aesthetics, like node overlaps. Side effects like these are not considered when optimizing in isolation but play an important role in task-solving. To support research analyzing the interplay of graph aesthetics for specific tasks, we extend our calculation to combinations of aesthetics. As an initial approach considering multiple aspects of viewport quality assessment simultaneously, we propose to linearly combine aesthetics contributing to a certain task and apply weights expressing their importance. The resulting combination can be calculated and visualized similarly as described in the previous sections for individual aesthetics. Additionally, we implemented a further visualization approach for the combinations, as described in Section 4.2.

To demonstrate and test task-specific viewport optimization using aesthetics combinations, we present exemplary compositions targeting the four most common task categories described by the task taxonomy of Lee et al. [46] and considered in other studies and applications [14, 16, 68]: *accessibility*, *adjacency*, *connectivity*, and *attributes* (see Table 2). The combinations are based on practical experiences and tests without claiming validity, and serve for demonstration purposes only.

3.3.1 Accessibility. *Accessibility* tasks involve identifying all nodes accessible from a given node, optionally with distance restrictions. To solve these tasks, edges should be easy to follow and identify, as optimized by the Edge Crossings (*EC*), Crossing Angles (*CA*), and Angular Resolution (*AR*) aesthetics. Moreover, nodes should be identifiable, as improved by the Node Overlaps (*NO*) aesthetic.

Table 1: Selected aesthetics with their corresponding abbreviations, work proposing or evaluating the aesthetic, and the goal, i.e, maximization ($\nearrow$), minimization ($\searrow$), or convergence ($\rightarrow$) to a certain value.

Abbr.	Aesthetic	Goal	Proposed/Evaluated by
EC	Edge Crossings	$\searrow$	[41, 59, 62, 64]
CA	Crossing Angles	$\rightarrow$	[33, 34, 80]
AR	Angular Resolution	$\nearrow$	[35, 60]
NO	Node Overlaps	$\searrow$	[18, 48]
TA	Total Area	$\searrow$	[5, 61, 69]
ML	Max. Edge Length	$\searrow$	[5, 69]
TL	Total Edge Length	$\searrow$	[5, 69]
UL	Uniform Edge Length	$\nearrow$	[5]

Table 2: Exemplary compositions of graph drawing aesthetics targeting four important tasks [46] in network analysis. While the relative weights are inspired by literature, the specific weights only serve for demonstration.

Task	Quality Measure Composition
Node Accessibility	$0.4\,EC + 0.3\,CA + 0.2\,AR + 0.1\,NO$
Node Adjacency	$0.4\,NO + 0.4\,AR + 0.2\,EC$
Node Connectivity	$0.4\,EC + 0.4\,CA + 0.2\,NO$
Node Attributes	$\sum_i w_i \cdot NO_i$

Prioritizing these quality measures, taking into account the relative importance of the measure discussed in Section 2.3, gives us an exemplary combination of $0.4\,EC + 0.3\,CA + 0.2\,AR + 0.1\,NO$.

3.3.2 Adjacency. Tasks related to *adjacency* consider nodes adjacent to a given node, e.g. counting the number of adjacent nodes. These tasks are negatively affected by nodes that are not clearly distinguishable (Node Overlaps), incident edges of a given node that are very close to each other (Angular Resolution), and edges that are hard to follow (Edge Crossings). Similarly, we arrive at the possible combination: $0.4\,NO + 0.4\,AR + 0.2\,EC$.

3.3.3 Connectivity. For *connectivity* tasks, connections between two or several nodes have to be identified (e.g., shortest path). These tasks mainly require the analyst to follow edges (e.g., Edge Crossings and Crossing Angles) and to determine incident nodes (Node Overlaps). Thus, we could use: $0.4\,EC + 0.4\,CA + 0.2\,NO$.

3.3.4 Node Attributes. Tasks focusing on *node attributes* mainly involve analyzing attributes mapped on node properties (e.g., finding a node with a certain value). For these tasks, it is essential that nodes are visible and not occluded (Node overlaps), while edges are of minor importance. By incorporating weights for attribute classes, the significance of individual attributes can be expressed. We could choose $\sum_i w_i \cdot NO_i$, where NO_i is the number of overlapping nodes with attribute i and the corresponding weight w_i.

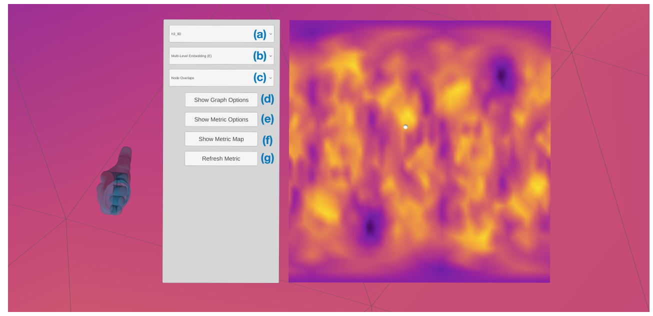

Figure 4: The menu panel of the application (left) and the 2D projection visualizing viewport qualities (right). The white dot indicates the current viewport. The menu supports the selection different graphs (a), graph layouts (b), aesthetic measures (c), graph visualization options (d), and different modifications for the quality measure calculation (e). Moreover, users can show or hide the 2D map (f) and refresh the aesthetic measure calculation after modifications (g).

4 APPLICATION

We implemented our approach in a VR system that can be accessed at `publication.joos.dbvis.de/2398`. With the application, we aim to establish a platform demonstrating our concepts, facilitating user studies, and serving as starting point for further research. In the following, we explain the application setup and design.

4.1 Setup

We decided on a Unity3D application in combination with the SteamVR framework, a highly flexible and widespread solution for VR applications. While most state-of-the-art VR HMDs can be used with this architecture, our setup uses the Valve Index with two hand-held controllers. The headset features a resolution of 1440×1600 pixels per eye, offering a comparably high field of view of approximately 130°. Limited room space is sufficient to run the application since physical walking is supported but not required.

4.2 Application Design

The goal of the application is to visualize 3D graph data and provide spatial navigation supported by aesthetic measures. While multiple file formats for **graph data** exist, the XML-based *GraphML* file format [9] is one of the most established ones supported by all major graph exploration tools. Hence, we decided on GraphML as the input format for our application. Users of the tool place their graph files in a predefined directory, which is scanned by the application on startup. These files are listed in a drop-down list that is part of a hand-held menu (see Figure 4 (a)) and can be selected by a virtual hand ray and a controller button.

After parsing the selected graph file, the nodes are placed within a fixed-sized space. For node placement, a user-provided, precomputed **layout** can be incorporated. Additionally, we have implemented an on-demand layout calculation feature. The modular structure supports arbitrary generation interfaces. For demonstration, we implemented a C++ interface using the open-source graph drawing library *OGDF* [13], providing efficient implementations for

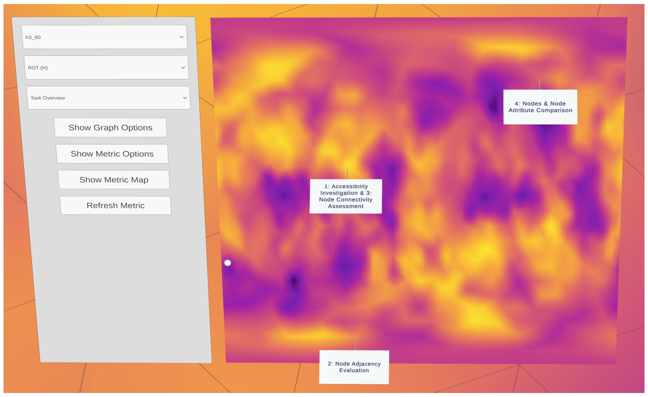

Figure 5: (a) The selection of optimized perspectives for individual tasks is supported by the task map. Annotations show the optimal viewport for all considered tasks.

many different graph drawing layouts. Our interface implements three of the most common 3D layout algorithms provided by the library, namely *Stress Minimization*, *Pivot Multi-Dimensional Scaling* (Pivot MDS), or *Multi-Level Embedding*. These layouts only target general graph structures, hence we implemented the *Reconfigurable Disc Tree* algorithm [39] designed for hierarchical graph structures. Layouts can be dynamically adjusted in the menu (see Figure 4 (b)).

For the **network visualization**, immersive graph exploration tools mainly rely on cubes or spheres to represent nodes and lines or shaded tubes for the edges [7, 42, 56, 78]. We chose to use spheres as they present a consistent appearance independent of the viewer's perspective. Similar to other approaches, categorical attributes are represented by node color (see Figure 1). For the edges, we implemented both lines and shaded tubes and let users change the representation in the graph drawing settings, which also contains options for the color mappings (see Figure 4 (d)).

Based on the 3D network representation and an icosphere surrounding the user, we implemented modular **aesthetics** calculation for isolated measures (see Table 1) and task-specific combinations (see Table 2). The granularity of the icosphere can be customized, a feature relevant to both the viewport quality calculation (as described in Section 3.1) and the visual representation. Quality measures can be selected using the hand-held menu (see Figure 4 (c)). Selected aesthetics or combinations are visualized by the icosphere and a 2D map (see Section 3.2). The color map visualizing the viewport quality can be customized, and a white marker displays the current viewport in both representations. Aesthetics, layouts, and weights (see Figure 4 (e)) can be adjusted as on demand, necessitating real-time calculation of viewport quality. For cases where live calculation is not fast enough, our application also supports caching and precomputation. To further support users in real-world explorations, we provide a **task map**. The task map visualizes the quality estimations for all task-specific aesthetics combinations that are implemented (see Table 2). For each combination, we calculate the global optimum and annotate it on the 2D map with a label always facing the user (see Figure 5). The background map visualizes the average of all selected aesthetic combinations.

The application supports various ways of **interaction**, and all standard VR controllers can be incorporated. Semi-translucent hands visualize the controller positions and gestures (see Figure 1). The options menu (see Figure 4 left) is attached to one hand and is only visible when the corresponding index finger touches the trigger. Pulling the trigger of the opposite hand displays a white ray, used for pointing at elements, while actions are activated by pressing a button. This interaction approach is simple and well-established in the field of VR applications. Similarly, users can point to a position on the 2D map or the icosphere surface and invoke the corresponding viewport change using a button click. Furthermore, viewport changes can be achieved by walking, moving the head, and using the joystick to rotate the graph structure. For viewport changes, the icosphere automatically rotates to match the new perspective, and the 2D map marker is adapted accordingly. To mitigate the risk of discomfort or VR sickness induced by the rotation, we display a fixed floor during rotations. Maintaining a constant spatial reference can reduce discomfort. [52, 65]. Further, we followed literature suggestions [58] to apply continuous movements with constant velocity without acceleration.

5 EVALUATION

We evaluate the applicability of our approach and demo application through two user studies involving security and biology experts. Their knowledge and experience regarding network exploration and the tasks they face make the experts' feedback highly valuable for assessing our technique. The first evaluation is of formative nature and aims to receive general feedback on the applicability of the approach while identifying modifications improving its practicality. The second study is more extensive and evaluates the system with aesthetic-driven navigation in more detail.

5.1 Security Experts

For our initial study, we were able to recruit six law enforcement agents together with network data modeled after their daily crime context. The domain experts each had multiple years of experience in analyzing and exploring graphs, mainly with 2D tools. Their tasks primarily relate to the graph topology, e.g., finding connections or non-connections between nodes. Further, investigating node attributes is of high relevance for their work. These task categories match the ones we consider for our task-specific aesthetic combinations. The initial study consisted of a 40 minutes slot, where all experts assessed the tool synchronously in a university laboratory. After explaining the overall problem, our approach, and the VR application, we briefly demonstrated the setup. Then, the participants explored the system. We incorporated a semi-structured interview asking for the relevance of the approach to the experts' workflow, suggestions for modification, and general feedback.

The overall feedback was very encouraging. The participants appreciated the opportunity to investigate network data in a S3D VR environment. They agreed on the benefits of the viewport optimization and especially favored the interactive selection of different aesthetic measures and their combinations. The experts argued that the task-specific viewport optimization using combined aesthetics has a high potential to support their different network exploration tasks, as the data could be perceived with less clutter. They further pointed out that the initial perspective can have a strong influence on the later exploration process, thus making the choice (and optimization) of the initial viewport crucial. Some experts highlighted that manual aesthetics changes and viewport selections required for task changes can be tedious. Thus, they emphasized the importance of our task map as a reasonable extension for speeding up the exploration process and the choice of the initial viewport, which all experts confirmed. Other comments suggested that standard analysis features such as filtering, searching, or clustering were missing. Some participants pointed out that this issue could be addressed by incorporating the approach as a plugin into existing immersive graph exploration tools like VRNetzer [56]. Thus, the value of our framework could be brought to existing applications already supporting fundamental and domain-specific analysis features.

The results of the initial study were encouraging and did not reveal significant issues with our approach. As the application and evaluation were meant to test our viewport quality estimation and aesthetic-driven navigation in isolation, explicit analysis tools were not included. However, as pointed out by participants, the approach could serve as a plugin for existing VR graph exploration tools.

5.2 Biology Experts

For the second study, we recruited three experts (E1-E3) from Biology, a different field than before, making the evaluation more diverse. Their daily work and knowledge made all participants potential users of a system incorporating our approach making their feedback highly valuable.

E1 reported five years of experience with network analysis and six to eight years considering proteins, molecules, and molecular dynamics. E1 is mainly concerned with the topology of protein-molecule interaction networks, typically having 20-40 nodes and a low density. The expert reported six years of experience with mathematical network analysis, four years with visual network exploration, and four years with biological networks.

E2 works with metabolic networks representing reactions in organisms. The networks are generally very large, with 5000-10000 nodes and varying densities. For the visual exploration, the expert extracts much smaller sub-networks and analyzes their structure.

E3 reported six years of experience with biological networks representing the interaction and social behavior of fish species. The expert works with small, low-density networks of around 15 nodes and is interested in centrality, paths, patterns, and other network properties that can be visually explored.

Asking for their expectations, E1 and E2 expected the tool to provide a small set of points or viewports that users could choose from interactively, leading to viewports with fewer perceptual issues. E3 expected the tool to provide more information about the quality of different viewports to support the user. In advance, we asked all experts whether they wanted to examine their own or synthetic data. All of them preferred artificial data.

5.2.1 Procedure. The study was performed in individual one-hour sessions in a university lab with a standard VR setup. After the consent and a background questionnaire, participants were briefed about the setup and application structure before initiating the evaluation using the HMD. The assessment comprised four tasks: two standard graph exploration tasks (with and without aesthetic assistance), task map evaluation, and free exploration. The tasks were aligned with the experts' knowledge and routine, covering the essential components of our approach, and corresponded to network analysis tasks identified by Lee et al. [46] that are similarly used in other studies (see Section 3.3). We created synthetic data with similar characteristics to the experts' data. Participants were encouraged to comment on their thoughts during the process.

The first task involved exploring a graph with 20 vertices to find the shortest path between two highlighted nodes with manual navigation, followed by enabling guided navigation with the Edge Crossings measures to evaluate its utility. The second task presented an attributed graph with 50 nodes showing categorical attributes with color. Participants were asked to manually find a good viewport for assessing the adjacency of three highlighted nodes. Then, they were assisted by the Node Overlap aesthetic, initially with default and later with user-defined weights. For the third task, participants tested the task map on another graph structure. After the prepared use cases, the fourth task allowed free exploration of the tool without constraints. For the last two tasks, arbitrary graphs ranging between 15 and 150 nodes with different densities and characteristics could be freely chosen by the participants. Following the practical evaluation, we gathered additional participant feedback through a semi-structured interview.

5.2.2 Results. During the first task, all experts aimed to minimize node occlusions and edge crossings by adjusting the graph's orientation. E2 also "tried to reduce edge occlusions". When the Edge Crossings aesthetic was activated, all participants confirmed its usefulness. E3 noted that purple-colored viewports were cluttered and obstructed paths, compared to yellow-colored viewports.

In the second task, all experts rotated the graph to decrease overlaps, particularly for highlighted nodes. E3 also tried to "reduce crossings of edges at the highlighted nodes and in general". Besides node overlap reduction, E2 rotated the graph such that "highlighted nodes were close" and edges connected to highlighted nodes had "no bad crossing angles". After activating the Node Overlap measure, all experts found the aesthetic aligned with their intuition on node overlaps and attribute-related tasks. E1 observed that purple-colored viewports led to "more node occlusion in general and more confusion in the entire graph". E3 also found these viewports "more chaotic, especially in the graph center", and "not very suitable" for the task compared to the yellow ones. The experts appreciated that they could adapt the calculation to match their current use case targeting nodes of a specific class. After applying a weighting, E3 commented that purple-colored viewports led to "way more clutter" concerning the target nodes. E1 and E2 also confirmed the advantages of yellow-colored viewports regarding node occlusions but argued that visibility issues still existed due to "edges occluding the nodes" (E1) and that "nodes were not close" to the observer (E2).

During the third task, all experts found the task map's ability to combine and optimize aesthetics simultaneously intuitive. E1 and E2 respectively mentioned that annotated viewports "matched well with the requirements for the tasks" and "were as expected".

In the fourth task, the experts appreciated interactive modifications of layouts, aesthetics, and graphs. E1 felt that the task map led to "advantageous viewports" that the expert "would have also chosen". E2 noted the potential for assessing layout algorithms using the tool and highlighted the similarity of the synthetic data to their own network data. E3 appreciated the color-mapped icosphere's usability, providing visual feedback, and found task map labels "always facing the user and becoming translucent during selection" helpful. To navigate to certain viewpoints, E1 and E2 only used the 2D map, while E3 favored both interaction techniques.

According to the questionnaire, the experts considered the Node Overlap (E1, E3), Edge Crossings (E2, E3), and Crossing Angles (E2) aesthetics to be the most valuable ones. E2 and E3 would have appreciated a further aesthetic incorporating the distance between users and nodes of interest. E2 also missed an aesthetic for reducing node-edge overlaps. When asked for their favorite application element, the task map (E1-E3), the 2D map (E1, E2), and the aesthetic weight modification (E3) were mentioned. The least used or liked feature was the sphere rotation (E1, E2).

The participants also raised critiques. E1 and E3 found the 2D map had to be held "far away to overview it completely", which "could be exhausting". E1 and E2 criticized that the icosphere surrounding the user "was not really intuitive" since the current viewport was behind and could not be seen without rotating the head. E1 would have appreciated larger labels for the menu and also mentioned that looking down on the graph can be "exhausting for the neck after a certain time". E2 found the joystick rotation challenging at first but could control it well after some practice. E1 reported slight dizziness after working with the application, while the other experts did not experience any discomfort. E2 mentioned that the fixed floor was "helpful for reducing discomfort" induced by the sphere rotation. E3 argued that the intense color map used for the icosphere could interfere with colors used to encode node attributes, which could be solved by "other colors with higher contrast".

Despite critiques, all experts agreed that the approach can enhance their network research and integrating it into existing VR tools would add significant value. Further, they suggested improvements, such as a visual zoom (E3), a "sphere miniature for navigation" (E2), and creating combinations of aesthetic measures for certain tasks directly in the application (E2). The experts also mentioned further application areas for the method, namely 3D molecule visualization (E1 and E3) and graph layout evaluation (E2).

6 DISCUSSION AND LIMITATIONS

The evaluation feedback was encouraging, showing that aesthetic-supported navigation can contribute to the exploration and knowledge retrieval process of domain experts. In addition to individual aesthetics, experts expressed a preference for examining viewports using task-specific combined aesthetics. The proposed viewports aligned well with experts' expectations and intuitions. The evaluations demonstrated that expert strategies (without aesthetic support) implicitly accounted for combined characteristics like node overlaps or edge crossings. This supports our idea of combining aesthetics for task-specific viewport optimization. The lack of research considering the effect of combined aesthetics on solving specific tasks limited us to demo combinations and encourages further research on this topic. While our evaluation suggests a potential for aesthetic-driven navigation, the approach can also be used to present optimized initial perspectives and automatically guide users without additional visual representation or interaction. Further, immersive data stories [37] may be created by animating multiple, automatically calculated viewports optimized to see interesting network features. Defining domain-specific aesthetics can transfer our navigation approach to other domains, e.g., 3D molecule analysis.

Besides minor technical issues that are easy to solve (e.g., label sizes or the 2D map distance), there were also general concerns. First, missing convenience features are justifiable by being a technique demonstration with an intended contribution as a plugin to existing tools. Including our method in these tools also solves the issue of "unintuitive" joystick navigation, as immersive graph exploration tools already contain manual navigation techniques. However, as pointed out by a study participant, further techniques like a miniature 3D sphere could be used to select viewports. There were also several concerns raised targeting the surrounding icosphere. Some experts criticized that–although technically correct–the icosphere representation visualizes the current viewport behind users, which could be misleading. Furthermore, the node and icosphere colors could interfere, the sphere rotation might cause discomfort (despite counter-measures like the fixed floor), and the participants mostly used the 2D map to navigate. Thus, we suggest making the icosphere temporarily hideable, which could also align better with the intended use as a plugin since graph exploration tools might use the space around a graph differently. Another concern targets the position of the graph, which requires frequent looking down. This issue can be addressed by allowing to move the graph visualization (and the surrounding icosphere), which has no effect on the quality calculation or navigation. Lastly, some experts identified further aesthetics of relevance, such as node-edge occlusion and distance of relevant objects. For a future version, we would like to add these measures and identify further aesthetics tailored to 3D graphs.

Despite careful consideration, our work comes with limitations. Due to the difficulty of acquiring a large number of domain experts, we could only conduct small-scale evaluations with six, respectively three, experts. Nevertheless, we are confident that their feedback shows the benefits of our work and improves it. We did not conduct a quantitative evaluation–despite its potential value–as the concrete usage was difficult to accurately quantify a priori and would not necessarily have enabled us to draw in-depth conclusions. Given the qualitative evaluation and conclusions available now, we could imagine conducting such a quantitative evaluation as part of the integration into existing tools. Before, research on task-specific aesthetic combinations and incorporating the results would be beneficial, as we could only consider exemplary combinations in this work. Despite having the opportunity to assess their own data, our experts preferred synthetic data. While the data was similar to their networks, a follow-up study should consider real-world data to increase the study's expressiveness. Regarding the calculation process and the mapping of the icosphere surface to the 2D map, we use some approximations that are not critical for most setups but should be carefully vetted on their applicability for other applications. We further rely on layouts that are perceived by an external user. For our evaluation, we focused on graphs with less than 100 nodes. This aligns with the real-world data of our participants and comparable VR user studies [7, 14, 78]. Moreover, this network size is already considered medium or large by other work [41, 45] as filtering and aggregation techniques are often applied before visually exploring networks [47]. The quality calculation can be performed in real time for the graphs we included. While this can not be achieved for significantly larger graphs, precomputation is supported, and methods based on deep learning can significantly speed up the calculation [29].

7 CONCLUSION

We presented a framework for 3D graph navigation based on viewport quality assessment. Our method incorporates major aesthetic measures reported by related literature and provides aesthetic combinations aiming to match common tasks. We developed two visual representations communicating the quality of viewports and allowing to switch perspectives easily, reducing unguided manual interaction. Our theoretical technique was implemented in an interactive VR application and evaluated by a two-stage expert study. The evaluation of the approach reveals that the implemented graph drawing aesthetics matched well with the expert's intuition. Their feedback showed that our method can contribute to the workflow of domain experts when exploring graph structure in the 3D space. Especially the task map providing optimal viewports for different tasks in a single representation was highlighted in this context.

In future work, we plan to integrate our approach into an existing VR graph exploration tool, add further aesthetics like node-edge overlaps, evaluate task-specific aesthetic combinations in more detail, and assess quantitatively how our navigation approach affects parameters such as efficiency, effectiveness, and task load.

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