https://doi.org/10.1016/j.aei.2023.102111

GazeGraphVis: Visual Analytics of Gaze Behaviors at Multiple Graph Levels for Path Tracing Tasks

Zhuo Yang[a], Yaqi Xie[a], Ming Li[b,c,*], and George Q. Huang[b,c]

[a] *School of Computer Science and Technology, Guangdong University of Technology, Guangzhou 510006, China*

[b] *Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong, China*

c. Research Institute for Advanced Manufacturing, The Hong Kong Polytechnic University, Hung Hom, Hong Kong, China

* Corresponding author: Ming Li at Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong, China, ming.li@polyu.edu.hk.

ABSTRACT

Graph visualization contributes to an efficient understanding of interconnected properties in graph data. However, the exponential growth of interconnections poses great challenges to the efficient visual cognition of graph data. Generation of expressive graph visualization requires investigations of the cognitive process of exploring graph visualization, which can be revealed through the analysis of gaze behaviors. In this paper, we propose GazeGraphVis, a visual analytics system, to analyze gaze behaviors for path tracing tasks. Specifically, GazeGraphVis visualizes gaze behaviors at multiple levels of graph, node and edge with overview+detail techniques to provide a comprehensive analysis of human cognitive processes when finishing path tracing tasks. The insights of gaze behaviors for path tracing tasks are revealed using an integrated multiple-view interface. Domain experts in visualization and eye tracking analysis gave high praise to GazeGraphVis for its capability of obtaining the overall search tendencies and deeply analyzing the factors that affect gaze behaviors.

Keywords: visual analytics, cognitive process, gaze behaviors, graph visualization.

1. INTRODUCTION

With the exponential growth of interconnected data, the processing of graph data is playing an increasingly critical role in every aspect of our lives [1]. Specifically, knowledge graphs are receiving much attention from researchers because they embed domain or interdisciplinary knowledge into fact triplets, which supports profound retrieval and reasoning based on relationships among entities [2,3]. For instance, fault diagnosis knowledge graphs help engineers locate failed parts of industrial assets through connections in efficiency and conduct maintenance tasks [4]. In educational scenarios, teachers use discipline knowledge graphs to achieve learning assessment, learning navigation, and personalized recommendation [5]. In knowledge graph analysis, searching for the shortest path between two specific entities is one of the most common tasks, and node-link diagrams are favored among prevailing graph visualizations for path tracing tasks because of their intuitive readability [6,7]. Hence, graph visualization is indispensable for analysts to learn about the topological information of graph data. However, a bad layout hinders knowledge graph users from obtaining information efficiently. Moreover, knowledge graph constructors and analysts in different domains lack graph visualization experience and knowledge of factors that slow down the efficiency of reading graph visualization, which prevents them from quickly generating decently readable graph visualization. Accordingly, the factors that influence individuals to perceive and explore graph visualization should be profoundly investigated to help them with the expressive visualization generation of knowledge graphs. Motivated by the above reasons, we consider devising an analytical framework to investigate how individuals explore graph visualization for knowledge graph constructors and analysts in different domains.

During the past decades, several efforts have been made to study how individuals explore graph visualization. However, most of them evaluate the performance of subjects' explorations on graph visualization in terms of speed and accuracy [8], which fails to embrace the intrinsic characteristics of the exploration, such as how edge crossings affect eye movements and what search strategies are applied. In addition, several researchers have used eye tracking technology to investigate human cognitive processes during graph visualization exploration but have not developed effective methods to process and analyze gaze data based on graph visualization [9].

To bridge the research gap, we consider eye tracking technology as an alternative solution to understand the human cognitive process of graph visualization exploration. Eye tracking technology reveals human cognitive processes by investigating an individual's visual perception, gaze behavior patterns and cognitive loads through gaze data [10]. Finding eye movement patterns provoked by different stimuli with various features is beneficial to understanding the characteristics of cognitive states, reactions and affections during explorations and further satisfying the demand of human-centered designs [11]. Therefore, it is imperative to develop a novel method to efficiently and effectively process gaze data based on graph visualization and intuitively analyze gaze behaviors from multiple perspectives to guide experts who construct domain knowledge graphs to generate readable graph visualizations.

This paper presents a visual analytics framework to derive and analyze gaze behaviors of an individual performing path tracing tasks in graph visualization from multiple graph levels. By understanding gaze behaviors for path tracing tasks, more practical points of view on how individuals obtain topological information as well as what search strategies are applied in the explorations can be appropriately extended, inspiring wide knowledge graph constructors to generate expressive and readable graph visualization. To achieve these objectives, we make the following contributions:

1. We propose a novel method to derive gaze behaviors based on graph visualization by expanding areas of interest on nodes and edges in gaze data processing.

2. We propose a novel approach for interactive visual analytics to inspect gaze behaviors at multiple graph levels from overview to detail for path tracing tasks and develop a visual analytics system called GazeGraphVis, which helps examine the cognitive process of exploring graph visualization.

3. We conduct an experiment that requires subjects to find the shortest path between a pair of source-target nodes in a graph with their gaze data recorded and gain a series of insights into individuals' search tendencies as well as the factors that influence their gaze behaviors with quantitative descriptions.

The remainder of the paper is organized as follows. Section 2 reviews the related work on gaze behaviors for path tracing tasks and the visualization of eye tracking data. Section 3 describes the gaze behaviors of interest, and the visual analytics framework and design rationales of the visual analytics system are proposed. Section 4 briefs the conducted experiment for path tracing tasks and introduces the proposed method of gaze data processing. Section 5 illustrates the visual analytics system called GazeGraphVis developed based on the proposed framework. Section 6 verifies the usability of GazeGraphVis from the perspectives of gaining profound insights and expert evaluations. Section 7 summarizes this work and prospects for future work.

2. RELATED WORK

2.1. Gaze Behaviors for Path-Tracing Tasks

Extensive research on how individuals read graphs for path tracing tasks has been conducted, and significant results have been identified. Helen Purchase [12] stated that reducing the number of edge crossings is essential for producing a graph drawing with effective aesthetics, while maximizing the minimum angle seemed less statistically significant. However, the tasks were not designated to find the shortest path. Rather, Huang et al. [13] argued that subjects responded faster when encountering a large crossing angle than when encountering a small crossing angle, indicating a great importance of maximizing the minimum crossing angle. In addition, Ware et al. [14] reported that path continuity suggested by the Gestalt principle of good continuation [15] was of great importance in perceiving shortest paths, and the edge crossings that crossed the shortest path had a moderate influence on the response time.

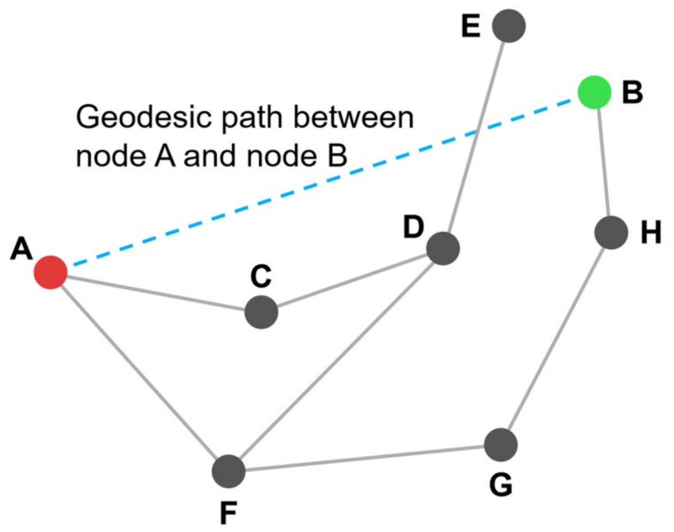

Figure 1. Illustration of geodesic path tendency redrawn with [11].

With the development of eye tracking techniques, Huang et al. [9] conducted an eye tracking experiment for path tracing tasks. By examining the eye movement videos, they discovered that eyes tended to follow the branch that was close to the geodesic path first when performing a path tracing task, which was regarded as geodesic path tendency. A geodesic path is a direct path between a source node and a target node, as Figure 1 shows. Dawson et al. [16] observed more search behaviors on prevalence of the closest-to-geodesic tendency, likely directions of search, revisitations, etc. However, without applying eye tracking techniques, the research obtained intuitions of the search process that were inaccessible. Although Huang et al. [9] gained new viewpoints on gaze behaviors for path tracing tasks, examining eye movement videos was not only time-consuming for analysis but also quite easy to omit details once analysts failed to keep up with fast eye movements. Therefore, a novel method to adequately visualize gaze data needs to be proposed for the efficiency and comprehensiveness of analyzing gaze behaviors for path tracing tasks.

2.2. Visualization for Eye Tracking Data

Substantial visualizations for eye tracking data were proposed to investigate gaze behaviors [17–19]. Blascheck et al. [20] reviewed eye tracking visualization with existing techniques and classified them into two categories: point-based methods and methods based on areas of interest (AOIs). Among these visualization techniques, scanpaths and attention maps are the most frequently used in the visual analysis of eye tracking data. Traditional scanpaths usually use circles to represent fixations and lines connecting two circles to represent saccades [21,22]. Due to their similarity with graph visualization, overlying traditional scanpaths on graph visualization hinders identifications by causing confusion and visual clutter [23]. In addition, traditional attention maps reveal overall attention distributions on the stimulus [24,25], leaving the temporal dimension of gaze data uninformed. Thus, traditional scanpaths and attention maps are not applicable for visualization gaze data on graph visualization.

In recent years, researchers have developed novel visualization techniques or visual analytics systems for gaze data targeting gaze behavior analysis on different stimuli. Kurzhals et al. [26] proposed the space-time cube (STC) to spatiotemporally identify gaze motion patterns of tracing objects when viewing a dynamic stimulus. Inspired by STC, Bruder et al. [27] presented space-time volume visualization, which derived stimulus context into volumes according to gaze data and visualized them in STC. Koch et al. [28] presented gaze spiral to visualize individuals' scanpaths based on video content, which benefited the identification of similar viewing behaviors. Breen et al. [29] designed a 2D and 3D gaze pattern visualization dashboard in a VR-based job interview simulator for educating interviewers to understand autistic individuals. Song et al. [30] proposed an interactive visual analytics framework to facilitate comparative gaze pattern analysis to investigate how radiologists read volumetric CT images in diagnosis. Wang et al. [31] developed a gaze data-driven visual analytics system to evaluate learners' learning engagement in MOOCs. Goodwin et al. [32] introduced a visual eye-tracking analytics (VETA) system to support the exploration of gaze patterns and behaviors involving gaze transition among AOI and saccades. Nevertheless, none of the state-of-the-art techniques have yet taken the interconnected characteristics of graphs into account in gaze behavior analysis on graph visualization stimulus, not to mention understanding gaze behaviors at multiple graph levels. Hence, it is necessary to develop a new approach of visual analytics for inspecting gaze behaviors regarding graph visualization in a qualitative and exploratory way.

3. BACKGROUND, DESIGN RATIONALE, AND SYSTEM OVERVIEW

3.1. Gaze Behaviors of Interest

Taking path tracing tasks into consideration, this work focuses on studying how individuals search as time elapses and how eye movements behave when gazing at nodes or edges. Therefore, we derive the gaze behaviors (GB) of interest, which are listed below:

GB1: Scanpath is worth investigating for the benefit of showing overall spatial attention shift during searching. Furthermore, it contributes to analyzing the search strategies and unconscious habits of a subject.

GB2: Gaze directions for the first hop on nodes indicate the directional tendencies of an individual finding the path between two nodes, which can be used to validate the angle range of search tendencies.

GB3: Gaze frequency and fixation duration on nodes and edges. The generally existing edge-edge crossings and node-edge overlappings in a graph visualization may confuse subjects and lead to longer exploration times. Therefore, we consider the frequency and duration with which a subject gazes at edges and nodes to determine how these crossings affect gaze behaviors.

GB4: Revisitation on nodes and edges expresses the repeated visit to a specific region, which can reflect that the region is informative or difficult for cognition.

3.2. Design Rationales

To support gaze behavior analysis, we consider developing a visual analytics system called GazeGraphVis. The design of GazeGraphVis is supposed to adhere to the design rationales described in the following:

R1: Support Explorations at Multiple Graph Levels. To obtain a comprehensive understanding of cognitive processes when finishing path tracing tasks, investigation of gaze behaviors at multiple graph levels is indispensable [33]. GazeGraphVis should support explorations of overall gaze behaviors from the whole graph [GB1] as well as scrutiny of gaze behaviors in detail at the node and edge levels [GB2-4] [34].

R2: Extend Visual Domain from 2D to 3D. As gaze data is spatiotemporal, gaze visualization can be of greater informative expression if it is extended by a temporal dimension from the spatial dimension. 3D space has been shown to be effective for visualizing the spatiotemporal characteristics of scanpaths [GB1] [35]. In 3D space, the gaze sequence is visualized as a series of 3D visual elements and displayed in chronological order, which causes less visual clutter than that in 2D visualization.

R3: Make Visual Encoding Intuitive and Consistent. Efficient analysis of gaze behaviors is challenged by the substantial volume of gaze data recorded in the experiments. To reduce the cognitive loads of analysts from different domains and clear barriers to understand complex domain-specific visualization, GazeGraphVis should employ custom visualization components for different types of gaze behaviors [GB1-4] [36]. Every visualization component should adopt intuitive visual encoding [37] to better express the characteristics of the gaze behaviors to analysts with different backgrounds as well as keep the color encoding consistent among them [38].

R4: Associate Interactions in Multiple Visualization Components. Collaborations among multiple visualization components is an available approach to access information of interest from various perspectives [39]. When interacting with one of the visualization components in GazeGraphVis, other visualization components should be associated with the corresponding interactions and highlight the related gaze data [33].

3.3. Visual Analytics Framework of Gaze Behaviors

We propose a visual analytics framework as Figure 2 demonstrates to facilitate comprehensive multi-level analysis of gaze behaviors on the stimulus that is graph visualization. The proposed framework has two core components, gaze data processing and gaze behaviors visual analytics. First, we process gaze data into different stages and expand nodes and edges' AOIs to derive gaze behaviors at graph, node, and edge levels respectively. Then, quantitative properties of graph visualizations are calculated based on graph data. Second, we visualize the interested gaze behaviors at multiple graph levels and quantitative properties of the graph with a visual analytics system called GazeGraphVis.

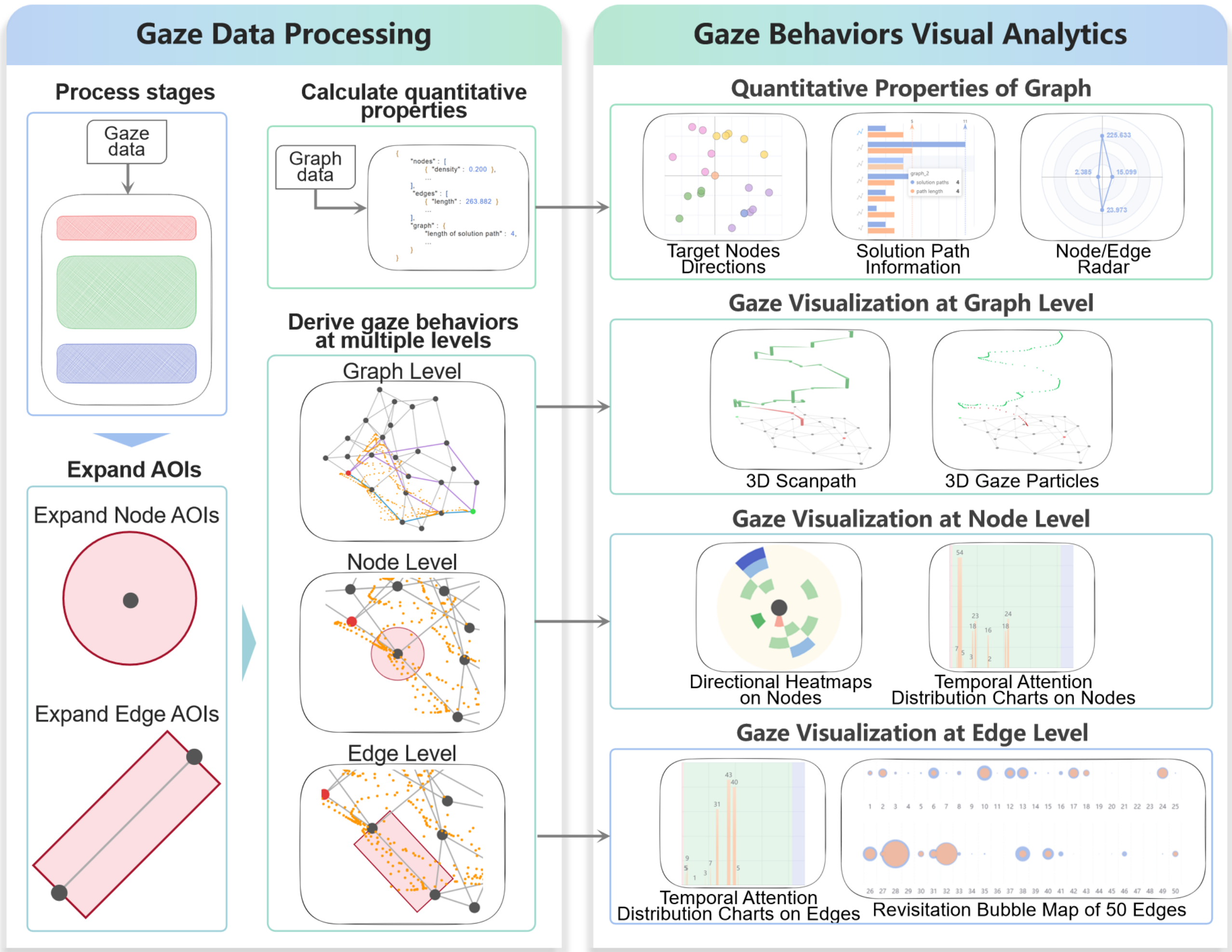

Figure 2. Visual analytics framework of gaze behaviors at multiple graph levels for the path tracing task.

4. EXPERIMENT AND DATA PROCESSING

To investigate the capability of the proposed visual analytics framework, we conducted a preliminary experiment to collect gaze data and devised a novel method to process gaze data based on graph visualization for further analysis.

4.1. Experiment for Path-Tracing Tasks

4.1.1 Graph Generation and Visualization

We generated the graph data and layout in advance for reproducibility. The graph data were generated using the Watts-Strogatz model [40]. The 20 generated graphs contain 25 nodes and 50 edges, which is intended to control the difficulty of tasks to a moderate degree. We also designated the source node and the target node, between which the length of the shortest path ranges from 3 to 5 hops for the same reason. Every graph has multiple solutions for the shortest path.

With respect to the visualization, the force-directed algorithm implemented in ECharts [41] was adopted for graph layouts. To ensure that the distance between the source and target nodes is moderate, we balanced the gravitational force and the repulsive force of the force-directed algorithm. In the layouts of 20 graphs, half of the source-target node pairs were positioned in vertical directions, while the other halves were in horizontal directions.

4.1.2 Participants

Ten participants (6 males, 4 females) majoring in computer science and technology were invited to join in the experiments by performing path tracing tasks. They all had normal or corrected-to-normal vision and did not have red–green blindness. Their first language was Chinese, and they habitually read from left to right and from top to bottom.

4.1.3 Path Tracing Tasks

In every trial, a graph with a source node ● and a target node ● was displayed on the screen. Subjects were asked to find the shortest path with a length within 5 hops in the given graph as quickly and correctly as possible. Once they found the shortest path, they should click the path in either ●→ ●→... →● → ● or ● → ●→... →● → ● order. During the search, we used the Tobii eye tracker to collect subjects' gaze data and cursor positions on the screen with a timestamp. The data were stored as csv files.

4.2. Gaze Data Processing

According to Duchowski [42], the pretreatment of gaze data is needed for consequent gaze visualization.

4.2.1 Process Gaze Sequence into Stages

Due to the substantial volume of gaze data, we attempt to process gaze sequence into stages according to the procedure of the experiment so that analysts can query and analyze gaze data by stage. We roughly divide the search period into 3 stages, which are the locating stage, searching stage and confirming stage, as Figure 3 shows.

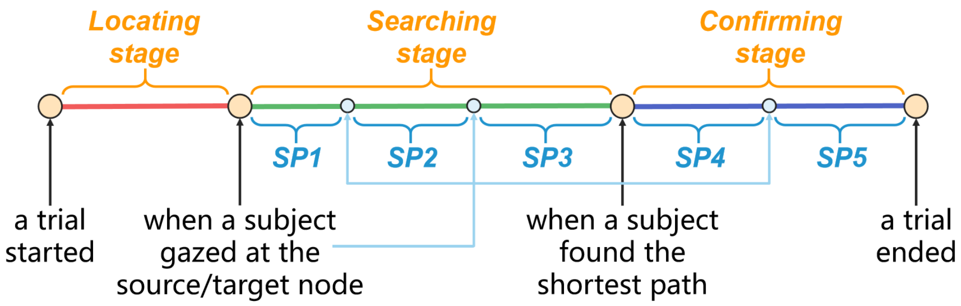

Figure 3. Each trial is mainly divided into 3 stages: locating stage, searching stage and confirming stage, while searching stage and confirming stage can be further divided into several search paths (SP).

Locating stage. Initially, subjects' gaze usually fell on the center of the screen and then moved to locate either the source node or the target node. This was probably because subjects gazed at the center area of the screen for preparation before the given graph was displayed. We separate it from the actual searching stage.

Searching stage. During the search, subjects began with either the source node or the target node to find the shortest path until they reached the other node or could not proceed. Therefore, we thought it was worth investigating every search path **(SP)** starting with either the source node or the target node to examine what stopped their search and the differences among several search paths. Hence, we further differentiated several search paths within this stage.

Confirming stage. When subjects found the shortest path, they began confirming answers by clicking nodes. We wondered about the relationship between gaze behaviors and mouse-based interactions. Therefore, we further divided this period into several search paths.

4.2.2 Expanded Areas of Interest

The perceptual span refers to the region where the information is obtained around the fixation point in visual perception. In the task of reading messages, the foveal region, which is the $2°$ of the visual field around the fixation point, contributes to the rapid processing of information [43]. The parafoveal region, the visual field of which ranges from $2°$ to $5°$ around the fixation point, can guide when and where gaze should move [44]. For visual search tasks, the stimulus within the span of effective vision that corresponds to the $5°$ around the fixation point can be accurately perceived [45].

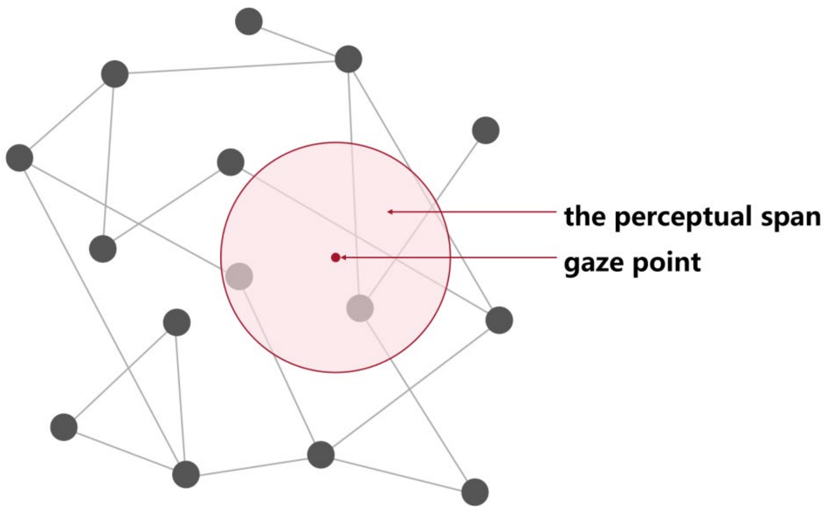

Figure 4. Although an individual's gaze does not fall precisely on a node or an edge, she or he can still perceive several elements within the perceptual span.

In our work, we consider one situation in which although the gaze point falls beyond the graphic region of the elements, individuals can perceive several elements within the perceptual span of the gaze point, as Figure 4 shows. In addition, the data error produced by the eye tracker should be properly tolerated to an extent in the analysis. Hence, we intend to expand the areas of interest (AOIs) of nodes and edges by the perceptual span to obtain the related gaze behaviors at the node or edge level, such as the perceived duration of every node and edge.

Whether the gaze point falls within the expanded AOI of a node can be determined using

$$\sqrt{(x_{g_t} - x_i)^2 + (y_{g_t} - y_i)^2} \le S_{perceptual} \tag{1}$$

where (x_{g_t}, y_{g_t}) denotes the coordinate of the gaze point at timestamp t, (x_i, y_i) denotes the coordinate of node i, and $S_{perceptual}$ denotes the perceptual span. It can be determined if the gaze point falls within the expanded AOI of an edge using

$$\frac{\left|Ax_{g_t} + By_{g_t} + C\right|}{\sqrt{A^2 + B^2}} \le S_{perceptual} \tag{2}$$

where A, B, and C are constants from $Ax + By + C = 0$, which denotes the connected edge between nodes i and j. Specifically, we set 60 px as the value of $S_{perceptual}$, which corresponds to the $2°$ of the visual field around the fixation point, as it is the most acute area to perceive and process information.

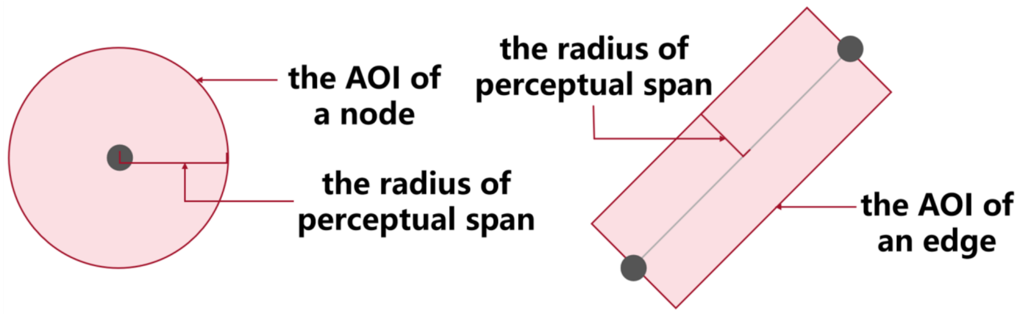

Figure 5. The expanded AOIs of a node (left) and an edge (right).

4.3. Derive Gaze Behaviors at Multiple Levels

We designate every node and edge in the graph an AOI, which helps easily map gaze data into graph stimuli. With these expanded AOIs, gaze behaviors on the nodes and edges [GB2-4] can be derived from raw gaze data and made visual analytics at the node and edge levels achievable. For instance, the hopping direction on a node [GB2] can be calculated as Algorithm 1.

Algorithm 1: Gaze Hopping Direction Extraction

Input: node n, gaze points $G = (g_1, g_2, ..., g_i, ..., g_n)$

Output: direction map d on node n

```
angles ← []
flag ← False
u⃗ ← (0,−1)
g_l ← Null
for g_l in G do
    if distance(g_l, n) ≤ S_perceptual then
        g_l ← g_i
        flag ← True
    else
        if flag then
            calculate angle α between u⃗ and <g_l, g_i>
            if len(angles) < 10 then
                push α into angles
            end
        else
            β ← average(angles)
            push β into d
        flag ← False
        end
    end
end
```

5. GAZEGRAPHVIS

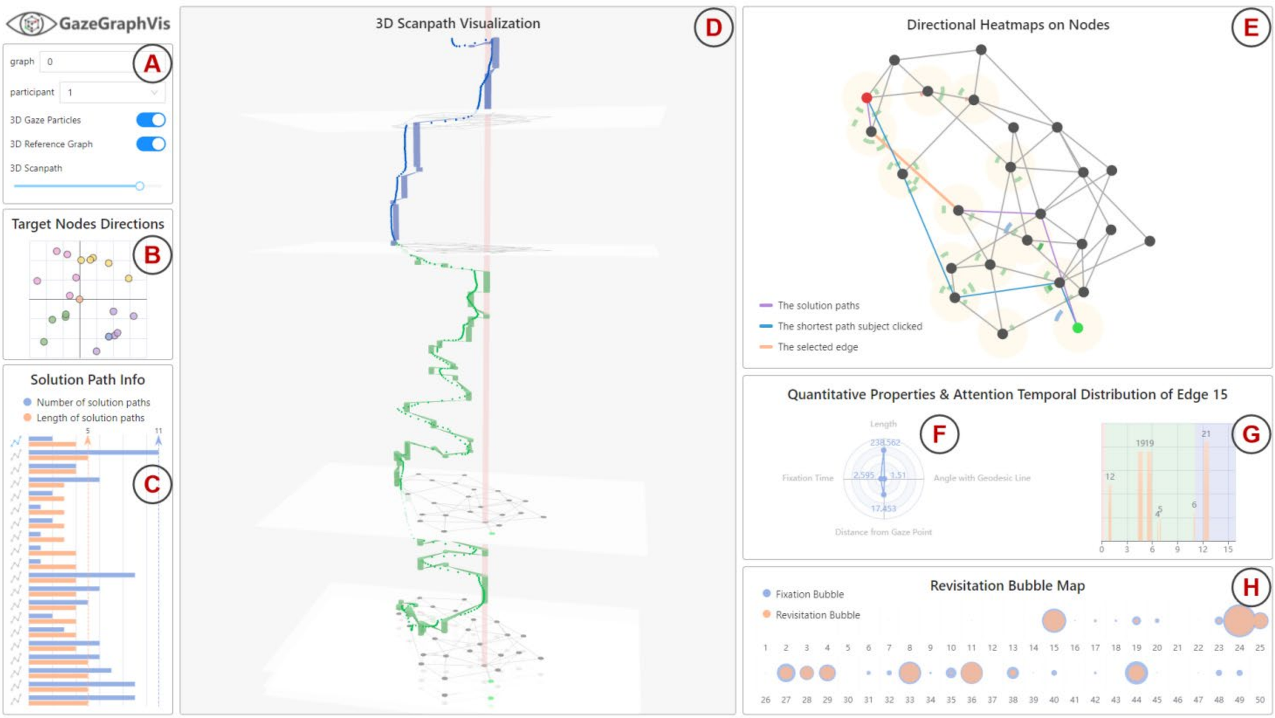

Figure 6. GazeGraphVis Overview. 3D Scanpath visualization, directional heatmaps on nodes, edge radar, attentive period distribution chart of edge 15 and the revisit bubble map of 50 edges are shown in components D, E, F, G, and H, respectively. Analysts can select different graph and gaze data of different subjects to analyze and control the 3D elements of 3D Scanpath in component A. Target Nodes Directions (B) illustrates the spatial distributions of the target nodes relative to the source node of all graphs, and Solution Path Info (C) illustrates the number and the length of solution paths of all graphs.

To facilitate visual analysis for gaze behaviors, we developed a visual analytics system called GazeGraphVis. As Figure 6 illustrates, GazeGraphVis consists of diverse visualization components (**VCs**) containing 2D and 3D visualizations to support comprehensive gaze behaviors analysis at graph, node, and edge levels for path tracing tasks on graph visualization. We explicate every VC and show how they meet the design rationales in the following.

5.1. VC1: 3D Scanpath Visualization

For the purpose of making a scanpath [GB1] spatiotemporally distinguishable on graph visualization, we extend the visual domain from 2D to 3D [R2].

5.1.1 Coordinate System of 3D Scanpath

Following the conventional 3D space-time cube design framework [46], we define the x- and y-axes as spatial dimensions and the z-axis as a temporal dimension, as shown in Figure 7. The (x,y) coordinate of a 3D visual element denotes the spatial position of its corresponding 2D element. The origin of the z-axis denotes the beginning of a search trial, and the z value of the 3D coordinate denotes the time that has passed since starting the tracing path, which enables chronological displays of the 3D visual elements.

5.1.2 Color Encoding of Search Stages

As discussed in Section 4.2.1, we divide the search period into 3 stages. As simply recognizable as it can be, we apply red, green and blue to represent the three stages [R3]. In addition, we color the cursor points with deep red for a flagrant contrast with blue because we only draw the cursor points of confirming stages. The color encoding we use is shown in Figure 7 (right), and it remains consistent when visualizing gaze behaviors by stage in other VCs, such as VC2 and VC3.

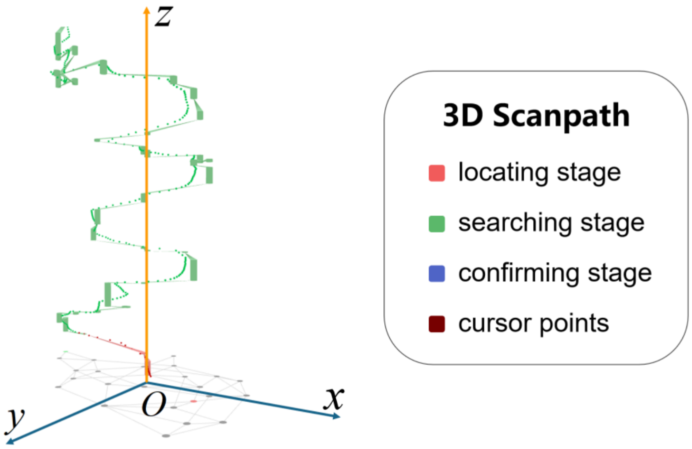

Figure 7. The coordinate system (left) and color encoding (right) of 3D Scanpath Visualization.

5.1.3 3D Visual Elements

3D Scanpaths. A 3D scanpath consists of a series of cylinders and oblique cones. A cylinder represents a fixation on a node [R1], whose height corresponds to the fixation duration. An oblique cone represents a saccade from node A to node B, whose apex points at node B's fixation cylinder. We stack cylinders and oblique cones in chronological order and place them on the spatial positions of the corresponding nodes (see Figure 7).

3D Reference Graphs. The topological information and the node coordinates of the graph provide strong support for the analysis of SP. Therefore, we draw the origin graphs with different z coordinates where every SP starts to provide an intuitive mapping between the 3D Scanpath and 2D graph for analysts [R3].

3D Gaze Particles. We visualize the raw gaze points chronologically as colored particles to give more details such as the subject's direct gaze position.

In 3D Scanpath Visualization, analysts are able to scale and rotate the 3D scanpath by controlling the mouse to inspect gaze data thoroughly (see Figure 6 (D)). They can set the visible states of the specific visual elements by a 3D controller (Figure 6 (A)) to pay more attention to the interested elements [R4].

5.2. VC2: Directional Heatmaps on Nodes

Directional heatmaps on nodes, which employ the system of polar coordinates, manifest the gaze directions hopped out every time on node [GB2, R1]. Every node of the graph is the pole of the polar system [R3]. The polar axis is regarded as a time axis, whose every unit stands for every SP, while the area around the pole is divided into 12 parts on average by angle. The intensity of the color in sectors is enhanced by the increase in the frequency with which the subject's gaze hops out from this node. In VC2 (see Figure 6 (E)), the graph in the search is shown with its solution paths and the shortest paths subject clicked highlighted. Analysts are able to change the visible state of the directional heatmap on a specific node by clicking on the node to avoid overlapping. Furthermore, the origin graph can serve as a navigator for further interactions with other VCs [R4], such as VC7.

5.3. VC3: Attentive Period Distribution Chart

We use modified bar charts to reveal the distribution of the attentive period that a subject spends on nodes or edges [GB3, R1] (see Figure 6 (G)). Every node and edge has its own bar chart. The background of the bar chart is colored as mentioned in Section 5.1.2 to represent periods of stages [R3]. The width of each bar represents the duration of the subject has perceived the element, and the height represents the number of gaze points that fell on the expanded AOI of the element during it is perceived. When a node or an edge is clicked in VC2, the bar chart displays the attentive period distribution on the clicked element [R4].

5.4. VC4: Revisitation Bubble Plot

To demonstrate the revisitation on the nodes and edges [GB4], we apply two bubbles with different radii to represent the total fixation duration (FD) and the revisitation duration (RD) on the same element [R3]. As RD is always shorter than FD, we lay revisit bubbles over the fixation bubbles to demonstrate the proportion of RD out of FD in contrast. With the displays of a series of bubble plots, analysts can easily obtain the regions that subjects searched repeatedly by comparison among bubbles (see Figure 6 (H)).

5.5. Visualization for Quantitative Properties of Graph

For quantitative analysis, simple charts are applied to visualize the quantitative properties of interest at multiple graph levels [R1, R3].

The direction and distance from the source node to the target node may affect subjects' search tendencies. We use a scatter plot (VC5) to compare the directions and distances of target nodes relative to source nodes in all graphs (see Figure 6 (B)).

Additionally, we are concerned about the answers of the path tracing task. The length and the number of the solution paths of all graphs are given by a bar chart (VC6) (see Figure 6 (C)).

At the node and edge levels, as their properties are independent, we use a radar chart to visualize them (see Figure 6 (F)). When a node is clicked in VC2, it displays a node radar (VC7) with the properties of the node, including its degree, fixation duration, number of crossings and density. When an edge is clicked in VC2, it displays an edge radar (VC8) with the properties of the edge, including its length, fixation duration, angle with geodesic line and average distance from gaze points [R4].

6. USABILITY STUDY OF GAZEGRAPHVIS

To investigate the ability of GazeGraphVis to analyze gaze behaviors for path tracing tasks, observations on gaze behaviors in path tracing tasks are expatiated with various visualization instances. Through analysis with GazeGraphVis, insights into search tendencies were gained, and suggestions for graph layout regarding topology-based tasks were given. In addition, we invited 5 domain experts to evaluate the design of GazeGraphVis and provide feedback regarding its usability.

6.1. Gaze Behaviors at the Graph Level

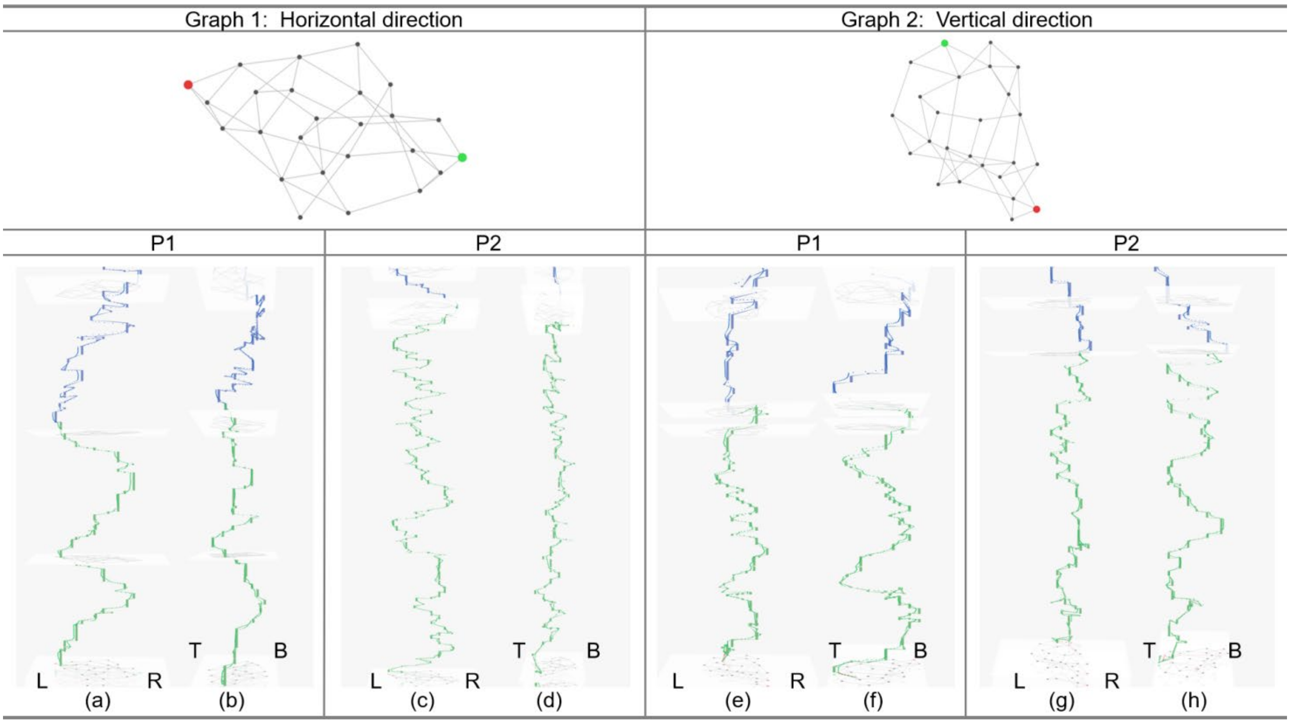

Figure 8. Comparison of 3D Scanpath Visualization of different subjects searching on different graphs. L, R, T and B denote the left, right, top and bottom sides of the graph, respectively.

The overall gaze behaviors are illustrated in Figure 8, which compares the 3D Scanpath visualizations of different subjects searching different graphs. Two graphs whose source node pairs lie in the horizontal direction and in the vertical direction are exemplified. To facilitate comparison, we show VC1 from the front and from the side in contrast.

In the locating stage, subjects did not always intend to find the source nodes ● to start with the task (see Figure 8 (e,f)). It is supposed that they just located the node whose color was obviously different from others quickly, regardless of what the color represented.

In the searching stage, although it reveals great differences in search strategies, similarities in search tendencies are found.

a. Individual search strategies vary

According to 3D Scanpath visualizations, it is obvious that Participant 1 tended to search continuously, while Participant 2 tended to search back and forth. As shown in Figure 8 (a,f), Participant 1 traced a path consistently from left to right (from top to bottom) when the target nodes laid in the horizontal (vertical) direction and then quickly shifted back to the beginning to begin a next search. In contrast, Participant 2 had quite a few repeated hesitant saccades between the target node pair, which contained dense nodes and edge crossings, as Figure 8 (c,h) shows. Due to the different search strategies applied, Participant 1 was able to obtain the answer as fast as possible, while Participant 2 was rather careful to search for other potential answers, resulting in a longer search time than Participant 1.

b. Common search direction - Geodesic Path tendency

Subjects were inclined to search in the direction in which the distance of the target node pair was relatively long. Taking Graph 1 as an example, the distance of the target node pair in the horizontal direction is longer than that in the vertical direction, and both participants subconsciously locate the source node ● and search from left to right in the beginning. As the geodesic path is the shortest direct distance between the target node pair, which was in the horizontal direction in this instance, participants searched from left to right so that they could reach the target node with the shortest distance. In Graph 2, the geodesic path is in the vertical direction, and both participants had dispositions to search from top to bottom. These results comply with the ***geodesic path tendency***. Furthermore, subjects spent more time searching the region just between and around the target nodes rather than the peripheral area of it. Presumably, this is because *subjects were reluctant to waste time searching regions that were not conducive to finishing the tasks*, such as the left region of the target node ●. It is likely to increase the shortest path length if subjects search from target node ● toward the left, which is adverse to the goal of path tracing tasks.

In the confirming stage, subjects' gazes moved first, and the pointer followed. It is speculated that when individuals use mice for computer interactions, they need their eye movement to obtain contexts so that their brain can guide hands to control where the cursor should go to perform a corresponding interaction, as shown in Figure 9. Apart from this, a few subjects still searched the path when they started confirming answers. This is probably because *the distraction of other nodes* *confuses subjects' short-term memories*. Short-term memory can hardly remember the complex distribution of nodes, which leads to a research in the complex region (see Figure 8 (e,f)).

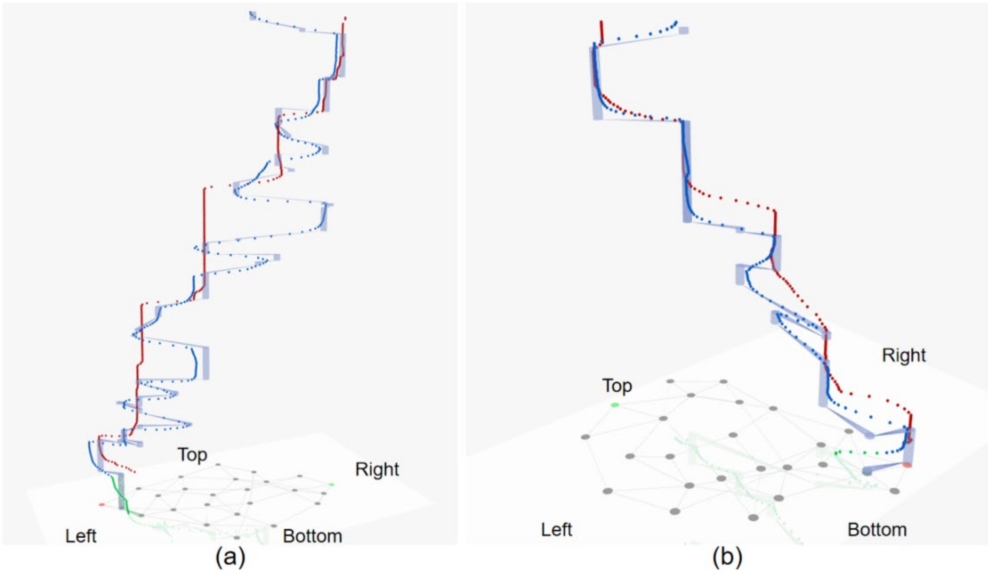

Figure 9. The subject moves eyes to obtain context before she or he interacts with the computer using a mouse. The opacity of the 3D Scanpath is adjusted to make the 3D Gaze Particles and 3D cursor points (deep red) clear.

6.2. Gaze Behaviors at the Node Level

We take gaze data of several subjects as examples to illustrate gaze behaviors at the node level using instances of VC2, as shown in Figures 10 and 11.

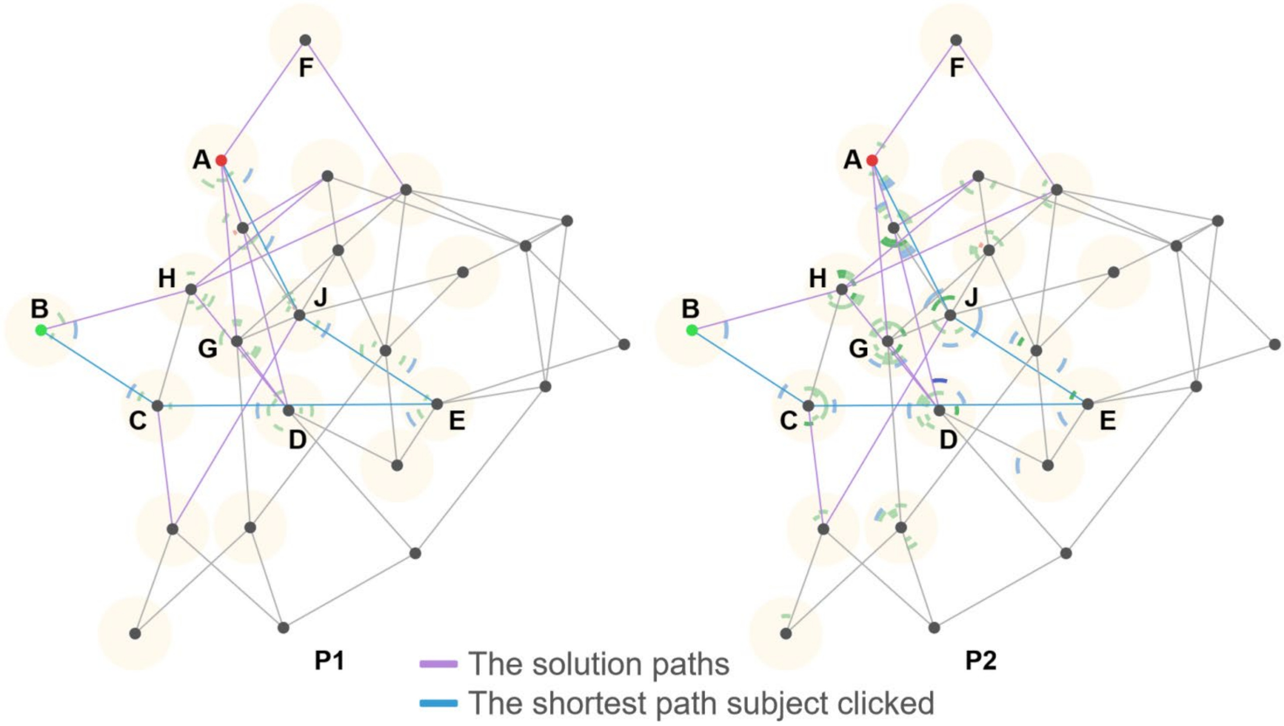

Figure 10. Comparison of two subjects' directional heatmaps in graph 15.

a. Left-right tendency & top-bottom tendency

In Figure 10, target nodes A and B are close to each other but have few nodes between them spatially. In light of directional heatmaps, Participant 1 started with node B on the left, followed the path B→C→E toward the right and returned to node J for his first search. This indicates that Participant 1 subconsciously searched from left to right until reaching E. The reason for turning back may be that the search direction toward the right was rather far away from node A, which does not reach node A with the shortest path. By comparison, Participant 2 began the search with node A and carefully checked downward to the edges around nodes H, G and D for a very long time. Complex connections, including edge crossings and node-edge overlappings, may be responsible for the increase in subjects' cognitive loads, which lead to repeated searches to obtain the context. There are two search tendencies***, left-right tendency*** and ***top-bottom tendency***, which have relevance to subjects' reading habits to a certain extent.

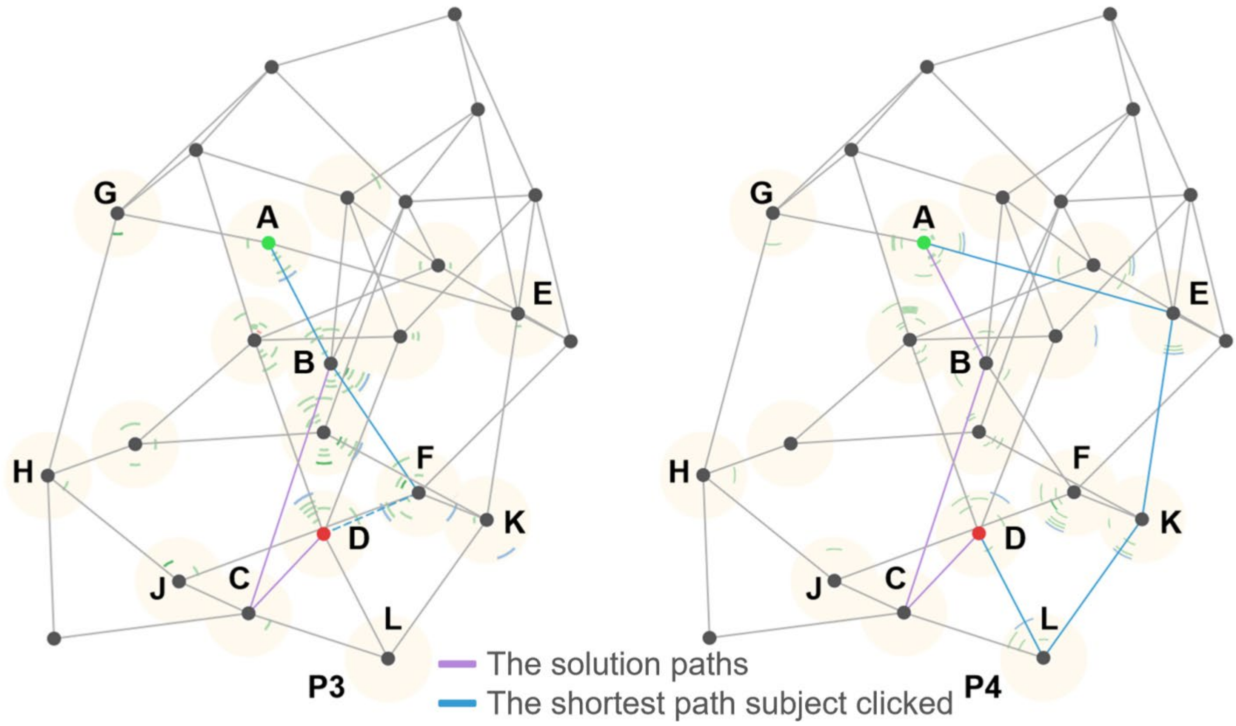

Figure 11. Comparison of two subjects' directional heatmaps in graph 5.

b. Sparse-Dense tendency

As Figure 11 illustrates, both subjects attempted to follow a path along A→B at first, which is the geodesic path tendency. After they failed to find an answer along the geodesic path owing to the complicated connections, they turned to searching in other directions from node A. They both attempted to trace along A→G→H→J, and Participant 3 returned to the region around node B, while Participant 4 traced along A→E→K→L. To comprehend the gaze behaviors that search far from the geodesic path, node radar is used. The densities of nodes B, G, H, E, and K were 0.24, 0.08, 0.08, 0.20, and 0.08, respectively. It can be speculated that subjects prefer to search a sparse region than a region of great and complex informativeness because they can obtain what they need simply for a glance and process it efficiently with low cognitive loads. The search tendency can be described as ***Sparse-Dense tendency***.

c. Node-edge overlappings had a negative influence on gaze behaviors for path tracing

As shown in Figure 11, Participant 3 chose an unconnected edge DF (the blue line of dashes) as an answer, which was completely misled by the node-edge overlapping of node D and edge FJ. This indicates that node-edge overlappings are hard to recognize and easily cause great distractions in path tracing tasks if careful attention is not paid.

6.3. Gaze Behaviors at the Edge Level

The gaze behaviors on edges are described with the demonstration of VC3 and VC4, as Figure 12 shows.

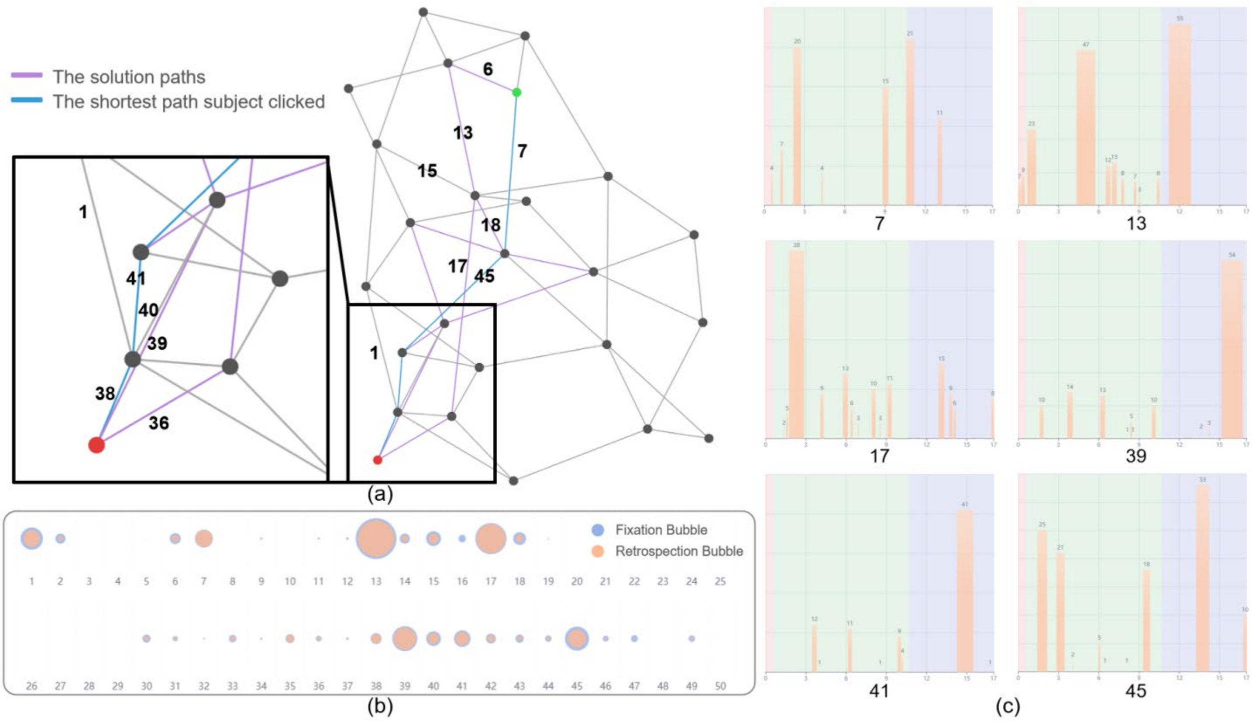

Figure 12. Revisitation bubble plot (b) and 6 attentive period distribution charts of specific edges (c) reveal gaze behaviors when searching in graph (a).

a. More attention was given to the longer edges with smaller angles from the geodesic path.

According to VC4 (see 12 (b)), the FD and RD of edges 1, 7, 13, 17, 39, and 45 are quite long compared to those of the other edges. Through observations on edge radar (VC8) of the edges mentioned above, the quantitative properties seem to share several common characteristics, as Table 1 shows. Not only are the lengths of these edges all longer than the average length of all edges, but the angles between the geodesic path and them are quite smaller than average. This suggests that longer edges with small angles from the geodesic path attract more attention, probably because edges with these properties can visually induce subjects to quickly approach the target.

Table 1. The lengths and angles with the geodesic path of the mentioned edges

Edge	Length (px)	Angle with Geodesic Path (degree)
1	225.612	34.857
7	280.820	16.456
13	234.842	32.257
17	385.594	14.669
39	263.929	5.362
45	247.512	25.274
Mean of 50 edges	188.899	83.071

b. Subjects tended to search consistently to maintain context continuity

As shown in Figure 12 (c), in the beginning, the subject focused around edges 7 and 13, which were close to the geodesic path. When gaze came to edge 18, connections became intricate because more branches and edge crossings appeared, which may surge the subject's cognitive loads. In the subsequent search, the subject invariably tended to search downward from along edges 7, 13 and 17 consistently until the node was reached. It can be presumed that rather than a depth-first search, subjects prefer a one-time consistent search many times in path tracing tasks. This search tendency has the advantages of maintaining context continuity in short-term memory as well as reducing distractions from crossings and branches, and it can be referred to as ***the consistency tendency***.

c. Fixation duration became longer during confirming answers

According to Figure 12 (c), the subject's fixation duration on several edges was rather long in the confirming stage. Analyzing with 3D Scanpath Visualization in combination, the subject located the nodes and waited for the cursor to move to the corresponding place before clicking by nodes to confirm answers. It is implied that waiting for the cursor to move and operate probably accounts for the longer fixation duration on edges.

6.4. Insights of Search Tendencies

Statistics on the occurrence frequency of assorted search tendencies attained in the analysis are performed. The results are classified based on the target node directions in graph visualizations, as Table 2 shows. Obviously, the Geodesic Path tendency is the most common search tendency in the path tracing tasks, which causes inclinations to search closely along the geodesic path. The consistency tendency is secondary to the geodesic path tendency as another important search tendency. Consistency tendency expresses the disposition to saccade consistently toward a specific direction for continuous path tracing, which is in accord with the principle of consistency in Gestalt laws [15]. When searching graph visualizations whose target node pairs are in horizontal directions, the left-right tendency is more conspicuous than the top-bottom tendency, while it appears to be opposite if the target node pairs are positioned in vertical directions. Although the SparseDense tendency is not noticeable, the statistics reveal that subjects tended to search a sparse region first and then a dense region in nearly half of the trials, which makes it a noteworthy search tendency.

Table 2. Frequency of every search tendency in the graphs whose target nodes lie in the horizontal and vertical directions.

Search tendency	Frequency		
	Horizontal	Vertical	Total
Geodesic Path	72.0%	79.0%	75.5%
Consistency	66.0%	70.0%	68.0%
Left-Right	84.0%	18.0%	51.0%
Top-Bottom	22.0%	84.0%	53.0%
Sparse-Dense	49.0%	49.0%	49.0%

6.5. Suggestions for Graph Layout

On the basis of five search tendencies and the factors that affect gaze behaviors, several suggestions about graph visualization layouts with regard to topology-based tasks such as path tracing tasks are given as follows.

a. Apply a consistent flow direction

In light of the consistency tendency, left-right tendency and top-bottom tendency, subjects are disposed to undertake a continuous search toward a specific direction. Hence, a consistent flow direction layout can be adopted for graph visualization with respect to topology-based search tasks, such as left-to-right or top-to-bottom flow directions. Transformation into tree visualization [47] is another alternative approach. Specifically, contemporary Chinese reads from left to right and then from top to bottom [48], which cultivates asymmetric perceptual span [49,50]. The perceptual region to the right of gaze points is larger, with greater ability to process information. Therefore, applying left-to-right or top-to-bottom flow directions for graph visualization is beneficial to increasing the efficiency of topology-based search tasks.

b. Distribute sparsely for significant nodes

In terms of the sparse-dense tendency, subjects can identify sparsely distributed nodes quickly during path tracing tasks. This is because the sparse distribution of nodes has low visual complexity, which induces a low cognitive load, and more memory resources can be used to process information and finish tasks [51]. Thus, for significant nodes such as nodes with high degree and important points, longer distances should be designated with neighbors to reduce visual complexity. Nodes with simple connections can stay close to their neighbors. This enables efficient cognition of significant nodes with great informativeness and peripheral nodes with simple connections.

c. Reduce edge crossings and node-edge overlappings

From the above analysis of gaze behaviors, edge crossings, especially those with acute angles [13], made these edges hard to distinguish and caused a time-consuming repeated search within a certain region. Moreover, node-edge overlapping misled subjects to identify a connection that did not exist by mistake, resulting in making a wrong answer. Therefore, it attaches great importance to distinguishing nodes and edges in topology-based search tasks. Reducing edge crossings and node-edge overlappings in graph visualizations is an available approach that is advantageous for clearly identifying nodes and edges.

6.6. Evaluation via Expert Feedback

To further evaluate the usability of GazeGraphVis to provide gaze behavior analysis for analysts from different domains, interviews with 5 experts (E0, E1, E2, E3, E4) were conducted. E0 is an expert focusing on computer graphics with more than 10 years of expertise. E1 is a three-year visualization researcher in the education domain. E2 and E3 are eye tracking researchers with three years of experience. E4 is an interdisciplinary researcher in the eye tracking and visualization domain with 7 years of expertise. One-on-one interviews for each expert lasted nearly one hour. First, we introduced the research background, the challenges encountered in the analysis of gaze behaviors regarding path tracing tasks and the objective of proposing the visual analytics framework and developing GazeGraphVis. Next, we explained the proposed method to expand AOIs of primitives and how to analyze with every visualization component. Then, experts were allowed to explore GazeGraphVis at will to perform gaze behavior analysis from graph, node, and edge levels and give certain findings about subjects' search tendencies, factors that influence subjects' gaze behaviors, etc. During their explorations, we adopted the think aloud method [52] to collect their immediate comments. Finally, we solicited suggestions on the analytical framework, visual design of each visualization component and interaction from experts. The feedback for GazeGraphVis is elaborated in functionality, comprehensibility, informativeness and scalability perspectives as follows.

Functionality. All experts agreed that the objective of GazeGraphVis for supporting gaze behavior analysis was properly fulfilled. E0 and E2 appreciated that gaze behavior visualizations were arranged at the graph, node and edge levels, which facilitated analysis from overview to details. E3 stated that the system was well designed to connect gaze behaviors with graph elements. E4 thought interactions among visualization components were useful, which enhanced flexible explorations to focus on the gaze behaviors of interest based on specific graph elements from different perspectives.

Comprehensibility. Most experts (E1, E2, E3, E4) agreed that GazeGraphVis was of easy comprehensibility and quickly acquired proficiency in it. E1 and E3 both liked directional heatmaps on nodes for intuitively displaying all saccadic directions on every node. E2 favored revisitation bubble plots for revealing important graph elements regarding path tracing tasks through comparisons. E4 preferred scanpath visualized in a 3D space over that in a 2D plane to maintain temporal characteristics of gaze data. However, E0 thought the design was complicated and worried about the steep learning curves. E1 thought 3D Scanpath Visualization could cause visual bias, and it was inefficient to keep adjusting visual angles in the exploration.

Informativeness. E2 thought the analysis for gaze behaviors of interest provided much inspiration. E1 mentioned that visualizations of quantitative properties related to graph elements contributed to attaining profound discoveries such as the sparse-dense tendency. In addition, experts provided valuable advice to GazeGraphVis. E2 suggested measuring cognitive loads by other gaze indicators, such as pupil diameter [53], to investigate which search region causes great pressure. E3 recommended taking the analysis of gaze behaviors based on topological paths into account. E4 advised that GazeGraphVis should involve structural characteristic analysis of graph visualizations in support of gaze behavior trait analysis when searching graph visualizations featuring diverse layouts.

Scalability. E0 mentioned that Revisitation Bubble Plots seemed to have poor scalability for comparing both durations regardless of their actual duration. E1 noted that 3D Scanpath Visualization would be overwhelmingly "tall" when the finishing time of the search was rather long, which was scarcely scalable. comparison among individuals. E4 reckoned that GazeGraphVis showed deficiency in group gaze behavior analysis owing to the lack of direct comparisons among participants.

Consequently, GazeGraphVis was evaluated to have the capability to analyze gaze behaviors from multiple dimensions and to benefit obtaining insights regarding the cognitive process of exploring graph visualization. However, the limitation of GazeGraphVis lies in its poor scalability to a certain degree and the impossibility of making a determinate conclusion on gaze behaviors due to the complexity and multiple potentials of human cognition. Despite the challenges, GazeGraphVis tries to provide a solution to make visual analysis of gaze behaviors for path tracing tasks feasible.

7. CONCLUSION

In this paper, we proposed a novel interactive visual analytics framework for gaze behaviors analysis on graph visualization stimulus, which includes gaze data processing and gaze behaviors visual analytics with a visual analytics system called GazeGraphVis. GazeGraphVis is a multiview visualization interface primarily including 3D Scanpath Visualization, Directional Heatmaps, Attentive Period Distribution Charts, Revisitation Bubble Plot and other visualizations for quantitative properties. GazeGraphVis provides support for analysts from different domains to comprehensively investigate the overall search tendencies at the graph level and detailed gaze behaviors on every node and edge, assisting them in understanding how individuals explore graph visualization and generate graph visualization layouts that adhere to the characteristics of human cognition.

A case study suggested that searching for the shortest path in graph visualization is a complicated process influenced by multiple factors. Individuals selectively apply diverse search strategies subconsciously so that they can adjust their search directions accordingly when confronted with different graph layouts. Domain experts in visualization and eye tracking analysis made thorough appraisals for GazeGraphVis, appreciated the capabilities of adequately expressing gaze behaviors to inspire striking insights concerning search strategies and gave certain suggestions on limitations.

In future work, we will attempt to upgrade GazeGraphVis to analyze gaze behaviors in groups for other topology-based tasks on graph visualization. By doing so, we envision obtaining a more profound understanding of human cognitive processes while exploring graph visualization.

ACKNOWLEDGMENTS

This research is supported by the National Natural Science Foundation of China (No. 52005218), the Projects of RIAM, PolyU (No. P0046130), and the RGC Collaborative Research Fund (No.C7076-22G).

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