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Short Paper

Gaze Attention and Flow Visualization using the Smudge Effect

Sangbong Yoo, Seongmin Jeong, Seokyeon Kim, and Yun Jang

Department of Computer Engineering, Sejong University, Seoul, Republic of Korea

Abstract

Many advanced gaze visualization techniques have been developed continuously based on the fundamental gaze visualizations such as scatter plots, attention map, and scanpath. However, it is not easy to locate challenging visualization techniques that resolve the limitations presented in the conventional gaze visualizations. Therefore, in this paper, we propose a novel visualization applying the smudge technique to the attention map. The proposed visualization intuitively shows the gaze flow and AoIs (Area of Interests) of an observer. Besides, it provides fixation, saccade, and micro-movement information, which allows us to respond to various analytical goals within a single visualization. Finally, we provide two case studies to show the effectiveness of our technique.

CCS Concepts

• ***Human-centered computing*** → ***Visualization techniques; Heat maps;*** *Human computer interaction (HCI);*

1. Introduction

Fundamental gaze visualizations such as scatter plots, heatmap, and scanpath are not complete enough for all types of gaze data analysis. Since the purpose of each visualization is limited to a specific analysis goal, there is a disadvantage that it is not easy to apply different types of analysis. Therefore, analysts employ various visualization techniques together to supplement insufficient information. However, since each visualization technique processes and displays data separately, the analytical approach using various visualizations concurrently tends to show various information separately without any connection. Thus, the use of multiple visualization techniques is not intuitive.

Recently, many visualization techniques that do not draw gaze data directly on visual stimulus have been studied [BKW13, KW13, KHH*15, Bur17, MVN*19]. On the other hand, the fundamental gaze visualizations, which map gaze data on visual stimulus, are not advanced much from the existing framework. In particular, gaze visualizations using the heatmap have not changed much from the past to the present. Many analysts utilize the heatmap visualization to analyze the attention of an observer, but the heatmap visualization does not provide gaze movement for the attention development analysis. Therefore it is challenging to evolve the heatmap visualization enabling the gaze flow analysis. Nonetheless, the heatmap visualization is the most intuitive gaze attention analysis technique since it shows the gaze data distribution directly on the visual stimulus.

In this paper, we propose a novel gaze visualization technique enabling to analyze gaze attention and flow using the smudge effect. We apply the smudge algorithm using a Gaussian brush tip to stretch the heatmap, which emphasizes the directionality in the data while maintaining the shape of the heatmap. Our gaze visualization allows us to analyze changes in the attention of an observer intuitively. Besides, since the proposed visualization contains fixation, saccade, micro-movement, and data movement, it is possible to perform efficient gaze data analysis within a visualization. Also, we analyze the gaze data using the proposed visualizations in the two case studies. Our research scope is to present a technique for simultaneously showing gaze data distribution and flow that has not been introduced in the fundamental gaze visualization.

2. Related Work

The fundamental gaze visualization techniques that the analysts utilize mainly include point-based, heatmap, and scanpath. Scatter plots represent raw gaze data as points. It is, therefore, difficult to analyze the sequence order and fixation time of the gaze data because the scatter plots render only the gaze positions. However, this visualization is often utilized for abstract data analysis since it is simple to visualize data and allows easy understanding of raw gaze data [SYKS13, SLK*16, HUB*19].

Scanpath visualization is an analytical technique that presents the gaze movements with nodes and links. The simplest way to visualize the scanpath is to connect all raw gaze points [BvRO19, FR19, OMTM*08, MCOMM13]. Blignaut et al. [BvRO19] adopt this technique for the smooth pursuit of the gaze. Fujii and Rekimoto [FR19] analyze gaze data adopting a method of connecting raw data points for the detailed gaze movement pattern analysis. Another way is to locate the fixations from the raw data and connect the fixation nodes with lines [KW16, DKZH19]. The visual-

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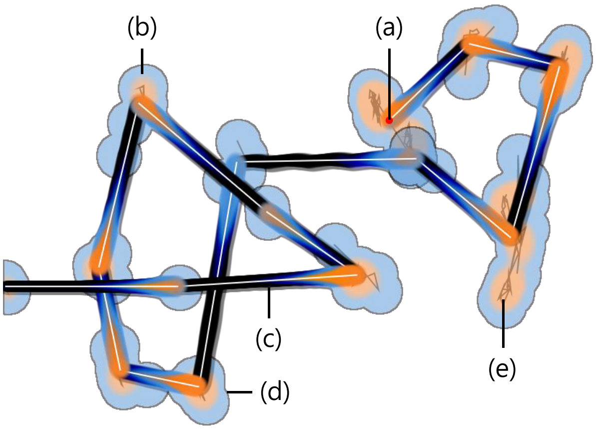

Figure 1: *The proposed gaze visualization. (a) is a start point of the gaze movement, (b) is a fixation, (c) is a saccade link, (d) is a contour, and (e) is a micro-movement within a fixation on the gaze.*

ization with fixations is less complicated than the technique of using raw gaze data since raw data points are clustered into fixation nodes. Therefore, more information, such as fixation time and directions, can be represented in saccade lines or fixation nodes. Fuhl et al. [PHT15] visualize similar gaze movement patterns between observers with color-coded links that indicate the gaze directions. Andrienko et al. [AABW12] encode the number of gaze visits to AoIs as link thickness and Kurzhals and Weiskopf [KW16] analyze the attention of an observer by revealing the fixation time as the size of the fixation node. Many scientists extract the fixations from raw gaze data and use them for the analysis [OMTM*08, MCOMM13]. However, relatively inaccurate location information might be provided for the analysis since a single fixation point represents many gaze points. Also, the longer the time to collect gaze data from the observer, the more the visual clutter occurs, similar to the way raw data is directly analyzed. Although bundling technologies can reduce visual clutter [PHT15], this scanpath visualization is still challenging to encode various gaze information.

Heatmap visualization is utilized to represent the distribution of gaze data. The heatmap is also called the attention map. The gaze distribution allows the analyst to examine how long an observer views the area of the visual stimulus [SM13, LSF*15, WKHA18]. The heatmap visualization is also used in the various visual stimulus analysis, such as the gaze data analysis in physical 3D shapes [WKHA18] and immersive video [LSF*15]. Smith and Mital [SM13] analyze how the gaze distribution changes according to the viewing conditions of video stimuli such as free-view and spot-the-location, and the scene types such as static and dynamic. However, since the heatmap visualization only shows the distribution of the entire data, it is impossible to analyze the gaze movements, nor can it analyze how the data accumulates in areas where the distribution density is high. For this reason, many analysts use different types of visualizations to analyze the fixation time according to the gaze movement in time order [BKT19, KZLK19, KBC*18]. Burch et al. [BKT19] propose a system for analyzing strategic eye movement patterns. Their system provides hierarchical flows showing the strategic viewing behavior aggregated over all scanpaths with a

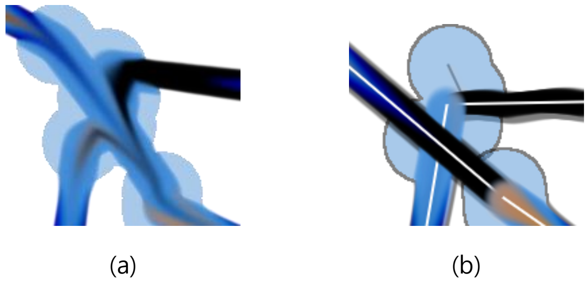

Figure 2: *Applying the smudge effect on the (a) heatmap and (b) layered heatmap.*

heatmap. Kong et al. [KZLK19] present accurate data location information by superimposing raw gaze data on a heatmap. Besides, by rendering the scanpath on the heatmap, it is possible to provide gaze data movement information that can not be analyzed by the heatmap alone [KBC*18].

Analysts often employ several fundamental visualizations for the gaze analysis since the visualization techniques vary depending on the data and purpose [BKH*11, SYKS13, NW16, NVA*17, HPH17]. Burch et al. [BKH*11] utilize the scanpath and heatmap, and Song et al. [SYKS13] apply the scanpath and scatter plots. Netzel and Weiskopf [NW16] adopt the heatmap and scatter plots for analysis. All of these fundamental visualizations are also often used [NVA*17, HPH17] together. Utilizing various visualizations expands the scope of analysis, which also increases the number of visualization types as needed. However, increasing the number of visualization types does not mean to improve analytical ability since it is only treating the data differently. Therefore, we need improved visualizations enabling easy analysis of gaze data. There is an attempt to devise advanced gaze visualization techniques. Peysakhovich and Hurter [PH18] propose a saccade visualization technique by drawing ink droplets that follow the directions on a flow direction map inspired by wind map and the Oriented Line Integral Convolution (OLIC). Li et al. [LYZ*18] propose a visualization by adding directionality to the heatmap. However, since the visualization technique by Peyaskhovich and Hurter [PH18] utilizes animations for more intuitive analysis, they do not show visual stimuli in the analysis. The visualization proposed by Li et al. [LYZ*18] is simply an extension of the circular heatmap core, which makes it difficult to distinguish between slow-moving data. Besides, it is difficult to apply it for the gaze analysis immediately since the visualization by Li et al. [LYZ*18] has not yet been studied in various cases. Therefore, we need more advanced visualization techniques to encode various gaze information.

3. Gaze Visualization

We apply the smudge effect to visualize the data flow in the gaze attention map. The smudge indicates a smearing effect in a specific direction [LBDF13]. The brush tip determines the smudge shape of an image. In general, the brush tip types used in the smudge technique include Gaussian, Dotty, and Hard edge. In this paper, we apply the smudge algorithm with the Gaussian brush tip. However, the smudge effect drawn first in the region where the movements

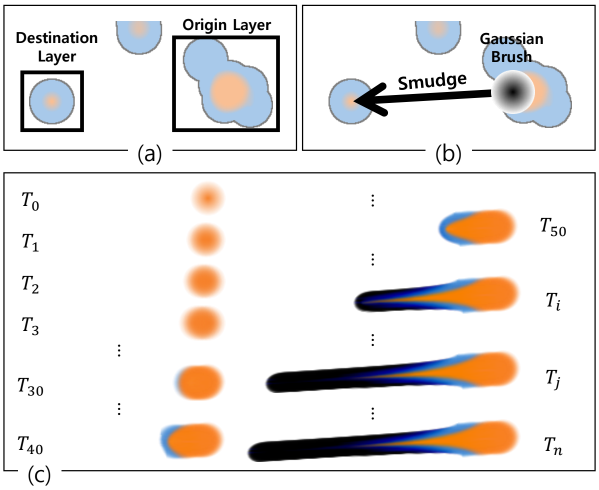

Figure 3: *The process of applying the smudge effect. (a) and (b) are brush generation. (c) shows how the smudge effect is produced.*

Algorithm 1 Smudge effect rendering.

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procedure SMUDGING:
    for layer ← HeatmapLayers do
        dx ← next_layer.x-layer.x
        dy ← next_layer.y-layer.y
        distance ← Math.sqrt(dx * dx + dy * dy)
        for i ← 0 to distance do
            ni ← i/distance
            px ← layer.x + dx * ni
            py ← layer.y + dy * ni
            generate_brush(brush, px, py)
            bsh ← brushSize/2
            ni ← (i + 1)/distance
            next_canvas.drawImage(brush, px, py − bsh)
        brush.clear()
        MainCanvas.drawImage(next_canvas)
```

overlap also affects the smudge effect drawn later as shown in Figure 2 (a). The initial data flow is changed by the smudge effect drawn later. Therefore, we separate the heatmap layers as shown in Figure 2 (b) to apply the smudge effect independently in order.

The heatmap layers are separated based on the fixation units. To distinguish the fixation layers, we assign the gaze data to the same fixation only when the time and position of the gaze data are adjacent. In general, the most established method for identifying fixations and saccades is the I-VT [SG00]. However, since velocity-based algorithms such as the I-VT use the only velocity threshold as a parameter, the influence of time cannot be considered in the fixation identification [YLB*16]. Therefore, we use the DBSCAN clustering algorithm [EKSX96] with the Interquartile Range [WWLT14] to obtain the minimum distance criterion in order to utilize the time information in the gaze data for the fixation identification. If the Euclidian distance of two consecutive points, P_i and $P_{(i+1)}$, is greater than the minimum distance, $Dist_{min}$, between the clusters in $Dist_{min} = Q3 \cdot 1.5 \cdot IQR$, $IQR = Q3 - Q1$, it is determined as an outlier, which is a saccade. Note that $Q1$ and $Q3$ indicate the distances of the first quartile (25%) and the third quartile (75%) gaze points from the center of the gaze distribution, respectively. When we identify the fixations with the DBSCAN algorithm from gaze data, which is time series data, we use $Dist_{min}$ as the scaling factor of the time-distance relation and use it as the time weight. Also, the fixations are extracted from raw data by setting epsilon as Q3, which is the minimum distance to be bound to adjacent clusters.

Figure 3 shows the process of drawing the smudge effect as illustrated in Figure 1 (b). In Figure 3 (a), the origin is the centroid of the 11th heatmap layer, and the destination is the centroid of the 12th layer. Figure 3 (b) displays the path where the Gaussian brush moves and smudges the image of the origin layer. Figure 3 (c) shows the process of smudging the origin layer by moving the Gaussian brush to the destination layer. Thus, the Gaussian brush that has not moved yet is created with the color and shape of the heatmap layer as seen in T_0 of Figure 3 (c). Algorithm 1 illustrates how to apply the smudge effect from the origin layer, T_0, to the destination layer, T_n, with Figure 3 (c). We interpolate the smudge effect by setting the source to the heatmap color and the destination to black, which is to distinguish between source and destination clearly. We set the destination color to black to make it distinct from the heatmap color. We first calculate the Euclidean distance between the origin heatmap layer and the destination layer to estimate the smudging distance. Then, we create the Gaussian brush at the centroid of the origin layer and move the brush by 1 pixel until it reaches the centroid of the destination layer. Finally, we overlay the Gaussian brush over the heatmap layer. We repeat this process for the entire heatmap layers.

We also add the white scanpath skeleton lines for highlighting saccade links as shown in Figure 1 (c) to distinguish the sequence order between the layers in the overlapping regions of eye movement. Besides, when many layers are separated within a certain area and the layered heatmaps overlap, it becomes very difficult to distinguish the fixations. Therefore, we add a contour to the heatmap as shown in Figure 1 (d) to display the fixations more intuitively. Also, micro-movement are repetitive eye movements within the fixation, allowing us to infer how much the observer is focused. We can utilize micro-movement to analyze the changes of the attention within the fixation as presented in Figure 1 (e). We identify the eye movement less than the minimum distance $Dist_{min}$ within the same fixation as the micro-movement.

4. Case Studies

We present two case studies to show the effectiveness of our gaze visualization technique. We have used five datasets out of the collected 34 gaze datasets from 23 observers. We have collected the data with the gaze tracking device Tobii Pro X2-30 [Tob19] (30Hz).

4.1. Comparison of attention developments

We compare the gaze of two observers using the heatmap and the proposed visualization. Figure 4 shows the gaze data of both observers. The visual stimulus viewed by both observers in Figure 4 is the cover page of the Pacific Graphics program book in 2018.

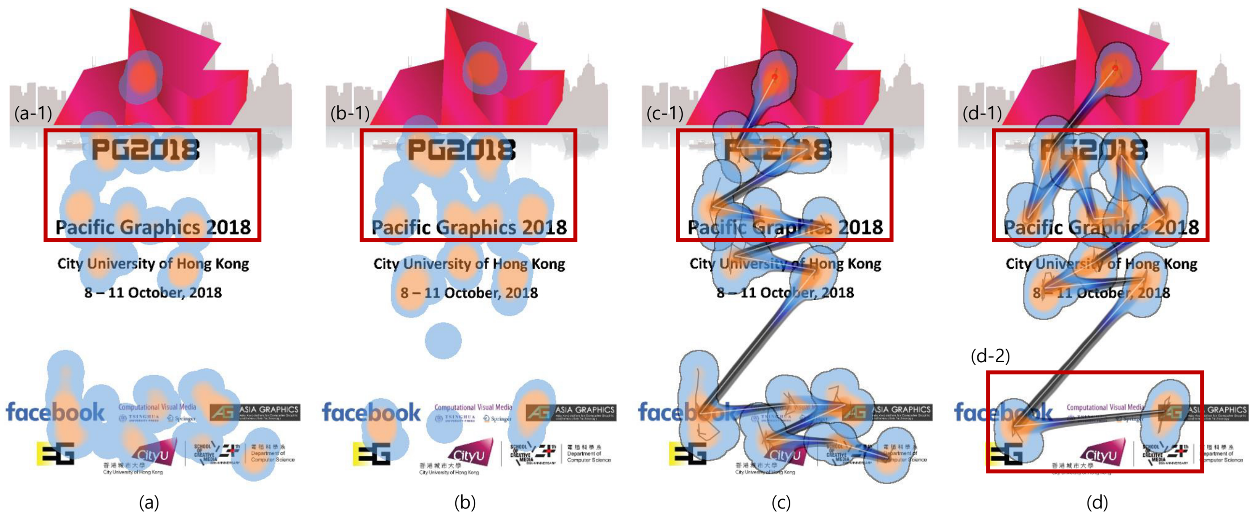

Figure 4: *Analysis comparison with the heatmap and our visualization. (a) and (b) are the heatmap describing gaze movement data of two observers. (c) and (d) are our visualizations. Note that (a) and (c) presents the data of one observer, and (b) and (d) show one of the other.*

Figure 4 (a) and (c) show the gaze data of the observer 1 with the heatmap and the proposed visualization, respectively. (b) and (d) are also the same visualizations for the gaze data of the observer 2. In the heatmap visualizations in (a) and (b), both observers looked at similar areas. The heatmap visualization shows that the observer 2 stares less in the sponsor area than the observer 1. We also compare the gaze data with the visualizations in (c) and (d) to analyze whether there is any difference in the gaze of the two observers. As shown in (c), the observer 1 shifts the attention from top to bottom. Similarly, in (d), the observer 2 also moves the attention from the top down. However, we can notice that the observer 2 does not look closely at the sponsor area at the bottom since there are few heatmap layers and micro-movement. Besides, (c-1) and (d-1) show different gaze movements of the two observers. The gaze movements in (c-1) indicate that the observer 1 moves the gaze to *Pacific Graphics 2018* after reading *PG2018*. However, in (d-1), the gaze of the observer shows alternating movements between *PG2018* and *Pacific Graphics 2018*. In this case study, we can verify that it is possible to discover gaze movements and patterns through the proposed visualization, which cannot be analyzed solely within the heatmap.

4.2. Gaze analysis using micro-movement

We examine the patterns and usability of micro-movement in gaze analysis. We have collected 13 gaze data for this case study using one visual stimulus. Figure 5 presents the visual stimulus we used in the experiment and the visualizations of three gaze data. Figure 5 (a) is a visual stimulus. (b), (c), and (d) are the gaze data visualizations revealing person-centered, background-centered, and balanced eye movement. The stimulus in (a) is a Korean classical painting, in which two young men watch the girls playing or washing their hairs in the valley. We have asked the observers to explain the painting. The observer in (b) said he found the young men in (a-1) and the stamp in (a-2). The observer in (c) did not find the young men but remembered the stamp. The observer in (d) recognized the stamp and the young men.

The task of the eye movement can be classified as an informational task while receiving information and navigational task in which trying to find specific information [CG07, GC07]. The eye movement of the informational task can be visible in the micro-movement. The observer in (b) tends to focus on human objects. The gaze remains at (b-1) where the young men are hidden, and the micro-movement show a pattern moving up and down. The gaze also stays in (b-2) even though the observer performs the person-centered search. (b-2) reveals a pattern in which the micro-movement move up and down. We cannot locate any other region where micro-movement move significantly compared to ones in (b-1) and (b-2). The observer in (c) views mainly backgrounds such as trees, valleys, and rocks rather than human objects. The observer did not mention the young men in the interview even though the gaze stays at (c-1). Therefore, we assume that we would not detect micro-movement near the young men, and this turns out that there is no micro-movement in (c-1). On the other hand, there are micro-movement in (c-2) where the stamp is located. The observer in (d) examines both the human objects and the background. The observer mentioned both the young men and the stamp in the interview. In (d-1), we notice the micro-movement at the stamp area. Therefore, we expect the micro-movement while the gaze stays in the area near the young men. However, we discover that, unlike what we have expected, the micro-movement stay only in the neighborhood, not in the area where the young men are.

This case study demonstrates how gaze behavior can be predicted through the micro-movement analysis. However, it is observed that the micro-movement cannot be a perfect indicator to predict gaze behaviors as seen in the exception case of (d). Therefore, it is not impossible to analyze and predict gaze behaviors using micro-movement, but further studies are necessary.

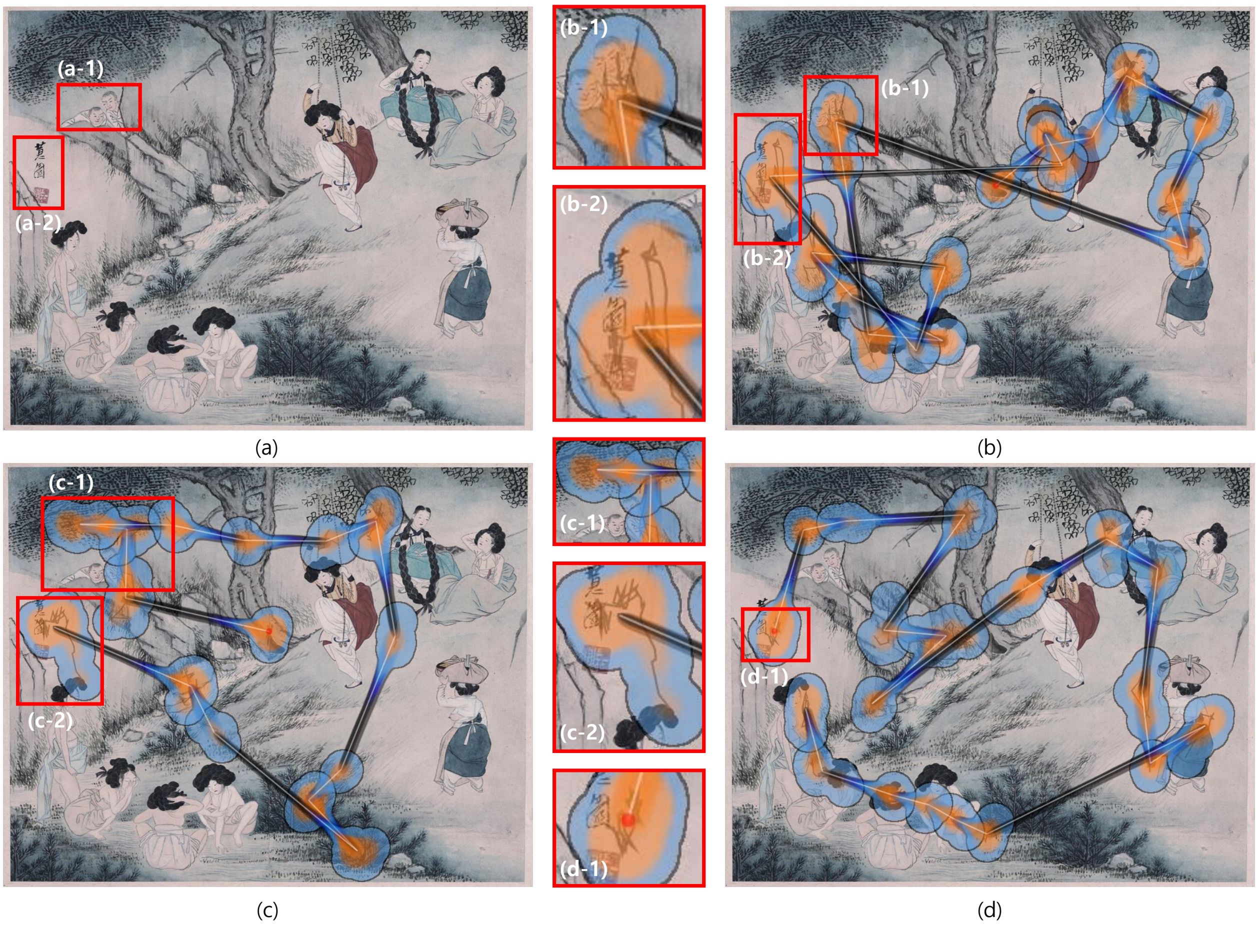

Figure 5: *Gaze behavior analysis using micro-movement. (a) is the stimulus. (b), (c), and (d) show the gaze data of three observers utilizing the proposed visualizations. The stimulus (a), "A Dano festival", is provided by Kansong Art & Culture Foundation in Seoul, South Korea.*

5. Conclusion

In this paper, we presented a novel heatmap-based visualization technique that shows the data flow using the smudge effect. The proposed visualization makes it possible to analyze the time series gaze data and intuitively render the attention and its development of observers. Also, the proposed visualization provides various gaze information such as attention with flow, fixation, saccade, and micro-movement, and enables more efficient gaze analysis within one visualization. We analyzed gaze data using the proposed visualization in the case studies. However, we need to discuss limitations such as the color map of the heatmap, merged fixation, a high degree of overdraw, scalability for higher data frequency, and visual clutter. We will investigate these limitations in the future. Moreover, we plan to explore more diverse case studies and evaluation to validate our gaze visualization.

Acknowledgments

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