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# Intuitive visualization technique to support eye tracking data analysis: A user-study

Vsevolod Peysakhovich  
ISAE-SUPAERO, Toulouse, France  
vsevolod.peysakhovich@isae-supaero.fr

Christophe Hurter  
ENAC, Toulouse, France  
christophe.hurter@enac.fr

## ABSTRACT

While fixation distribution is conventionally visualized using heat maps, there is still a lack of a commonly accepted technique to visualize saccade distributions. Inspired by wind maps and the Oriented Line Integral Convolution (OLIC) technique, we visualize saccades by drawing ink droplets which follow the direction indicated by a flow direction map. This direction map is computed using a kernel density estimation technique over the tangent directions to each saccade gaze point. The image is further blended with the corresponding heat map. It results in an animation or a static image showing main directions of the transitions between different areas of interest. We also present results from a web-based user study where naive non-expert users were asked to identify the direction of the flow and simple patterns. The results showed that these visualizations can successfully be used to support visual analysis of the eye-tracking data. It also showed that the use of animation allows to ease the task and to improve the performance.

## CCS CONCEPTS

• **Human-centered computing** → **Visualization techniques; Information visualization;**

## KEYWORDS

Scanpath, visualization, flow directional map, Oriented Line Integral Convolution.

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## 1 INTRODUCTION

The first step of the eye tracking data analysis is often the visualization of the raw data [Holmqvist et al. 2011]. By observing the generated image, the investigator can verify the distribution of the sampled points and verify the correspondence of the densest, i.e. most viewed, areas to some salient stimulus parts. Fixation distribution is conventionally illustrated using heat maps [Špakov

and Miniotas 2007]. A convolution of a small symmetrical kernel with the data points gives an intuitive representation of the most viewed stimulus areas. The width of the kernel allows taking into account the imprecision of both eye tracking device and the fixational eye movements during which a human eye is never still. The lower is the accuracy of the eye tracker, the larger should be the kernel. However, generating such an intuitive illustration of the transitions (or saccades) between these most fixated areas is less straightforward.

While numerous visualization approaches exist [Blascheck et al. 2014], none of them proposes an intuitive visualization technique for scan paths. Commonly used gaze plots depict saccades as straight lines that connect fixations shown as small circles. This straightforward representation can show if there is a connection between two areas of interest or not. It is an efficient visualization method for small datasets [Goldberg and Helfman 2010b]. Unfortunately, the gaze plots become increasingly cluttered when the number of saccades goes up [Eraslan et al. 2015]. But mostly, an important drawback of this visualization method is that it cannot immediately convey the crucial information of the transitions – their direction.

Recent works proposed to overcome these drawbacks by visually simplifying the drawing and aggregating transitions according to their directions and spatial proximity [Goldberg and Helfman 2010a; Peysakhovich and Hurter 2018; Peysakhovich et al. 2015]. It is based on the mean-shift algorithm [Comaniciu and Meer 2002] applied both to the fixation points and the saccades. An accessory product of these visual aggregation techniques is the concept of flow direction maps that allows grasping the locally dominant directions of the eye movements in a vector field. The generated two-dimensional vector data can be visualized in a single image using the Oriented Line Integral Convolution (OLIC) technique [Wegenkittl et al. 1997].

The "holy grail" of the eye tracking data visualization is a method that would intuitively convey the directional information in a similar way the heat map conveys the density information. Inspired by wind maps where the directions are depicted using OLIC technique with temperature maps depicted underneath the wind information, we wanted to verify the intuitiveness of these visualizations applied to the eye tracking data. In this preliminary study, we performed a web-based survey aimed to answer two questions: 1) Without any particular instruction nor training, is it possible to understand the flow direction depicted using the OLIC algorithm? and 2) Based on the eye tracking data, is it possible to identify transitions between different areas of interest from a static image?

The paper is structured as follows: after a brief description of the flow direction maps concept and presenting the pipeline of the visualization, we present the survey design and its results. We then discuss the results and conclude on future possible extensions.

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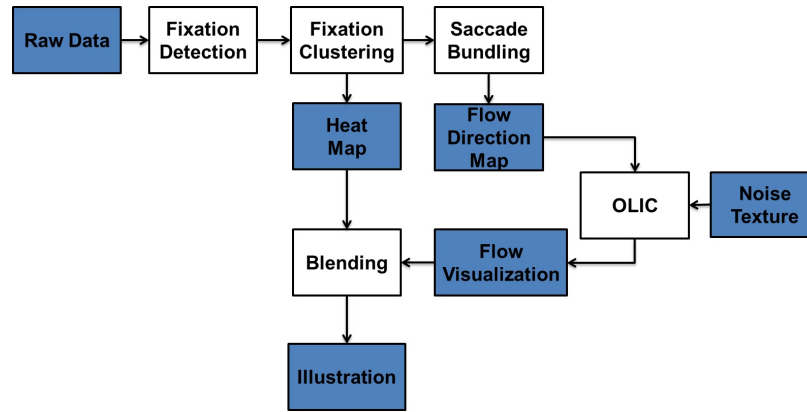


Figure 1: The pipeline of the flow visualization using the OLIC algorithm and visual aggregation techniques.

## 2 EYE MOVEMENTS FLOW DEFINITION AND VISUALIZATION

The flow direction maps [Peysakhovich et al. 2015] can be used to determine locally dominant eye movements directions. These maps are constructed similarly to attentional maps using the kernel density estimation technique. At each saccade sample, the radial kernel  $K(\cdot)$  is multiplied by the vector component  $(s_{j+1} - s_j)$  – an estimate of the unit tangent vector to the point of a saccade  $s_j$ . Thus, the map  $\theta(\cdot)$  is defined by

$$\theta(x) = K(x) * \sum_j (s_{j+1} - s_j) \cdot \delta(x - s_j).$$

The flow direction maps are used to perform saccade bundling and are refined at each step of the iterative process.

The pipeline of the technique is presented on the Figure 1. First, the fixations are extracted from the raw data [Andersson et al. 2017], and are then clustered together using the mean-shift algorithm [Comanicu and Meer 2002]. At this step, attentional maps are generated using the density maps. Following [Peysakhovich and Hurter 2018], we used maps with a resolution of  $420 \times 420$  pixels and a kernel width of 31. Thus, a  $4 \times 4$  pixel square on the screen corresponds to one map cell. We used neighborhood width of 40 to compute the gradient to the local densest area. At each iteration, samples are moved according to the gradient. We performed 10 clustering iterations.

Second, the saccades are bundled together using both directional information from the flow direction maps and spatial information from conventional density maps. The procedure is similar to the fixation clustering, except that now the points of the saccades are shifted instead of the fixations. The directional compatibility is computed as a maximum allowed angle between the local direction (as defined by the flow direction map) and the point direction. We performed 20 saccade bundling iterations using the similar settings as for the fixation clustering.

After performing the fixation clustering and saccade bundling, heat map and flow direction map are available. While heat map is a 2D texture and can be displayed directly, the flow direction map is stored in two textures. Therefore, as proposed by [Peysakhovich and Hurter 2018], we visualize it in a single 2D image using the Oriented

Line Integral Convolution (OLIC) method [Cabral and Leedom 1993; Wegenkittl et al. 1997]. This technique uses a noise texture as an input and visualizes vector fields by drawing ink droplets following the local flow direction. A ramp-like one-dimensional kernel is used to visually accentuate the "tails" of streamlines. By shifting the ramp by one of a few pixels, the textures can be animated.

Eventually, the flow visualization using OLIC technique and the heat map are blended together to obtain a single 2D image containing the information about both fixations and saccades.

## 3 WEB-BASED USER-STUDY

### 3.1 Participants

For the first part of the experiment (direction perception), the participants were 32 volunteers (10 females, age  $29.1 \pm 4.7$ ), recruited through social networks (LinkedIn, Twitter, Facebook). All participants had no previous experience in visual analytics or visualization domains and were naive relatively to the goal of the experiment. All participants gave their informed consent before starting the survey and were free to stop it any time.

For the second part (pattern perception), the participants were randomly assigned to Group 1 (15 volunteers, 3 females, age  $28.3 \pm 2.6$ ) and Group 2 (11 volunteers, 2 females, age  $30.9 \pm 6.8$ ). Group 1 was presented with the static condition (cf. Sec. *Survey design*), while Group 2 was presented with the animated condition. Five participants aborted the survey after completing the first part of the experiment.

### 3.2 Survey design

The survey was implemented online using browser-based PsyToolkit ([www.psychtoolkit.org](http://www.psychtoolkit.org); [Stoet 2010, 2017]). It is a free-to-use toolkit that allows to design and run questionnaire surveys online. The browser-based version of the survey was chosen in order to reduce the survey time and also to verify the feasibility of performing in the further a larger survey involving a big number of participants.

*Direction perception.* In the first part of the experiment, participants were asked to determine the flow direction for each of the 8 presented stimuli (Fig. 2). The answers were depicted as arrows

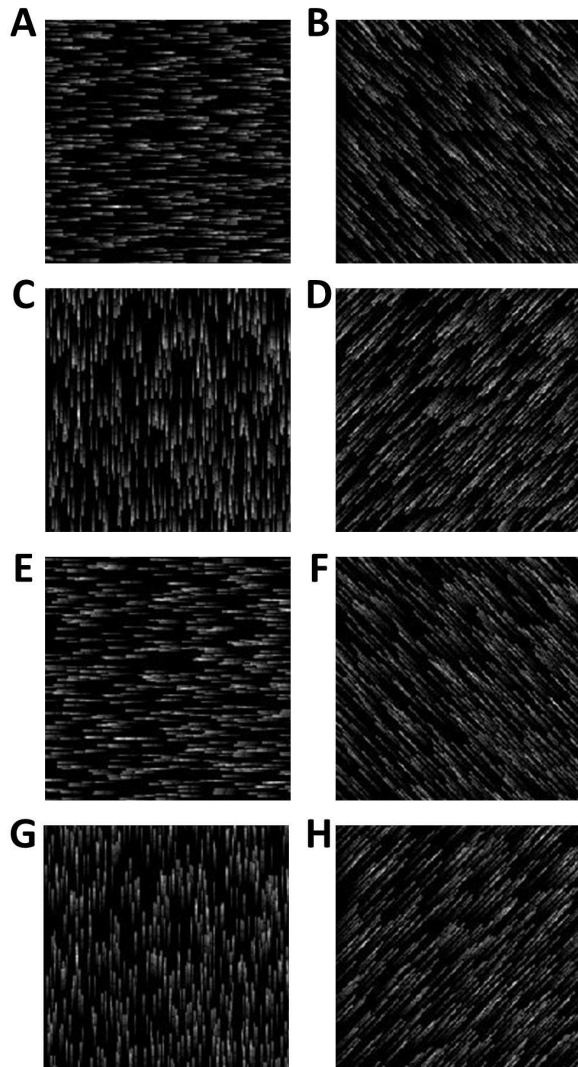


Figure 2: Flow visualization using the OLIC algorithm for flows of different directions. A) The flow angle is equal to 0°, B) 45°, C) 90°, D) 135°, E) 180°, F) 225°, G) 270°, H) 315°.

in the corresponding direction with only one answer possible. For each direction, participants were then asked to evaluate the difficulty of the decision on the scale from 1 (very easy) to 5 (very hard). The order of questions was randomized. The data corresponded to uniform generated vector fields. This part of the study was used to evaluate the understanding of the flow visualization per se, without any real-world meaning.

*Pattern perception.* In the second part of the experiment, participants were asked to check all transitions of different directions that they could spot using the provided visualizations for the square pattern (Fig. 3) and an observation of the Michelangelo masterpiece (Fig. 4). The eye-tracking data used to generate the visualizations are

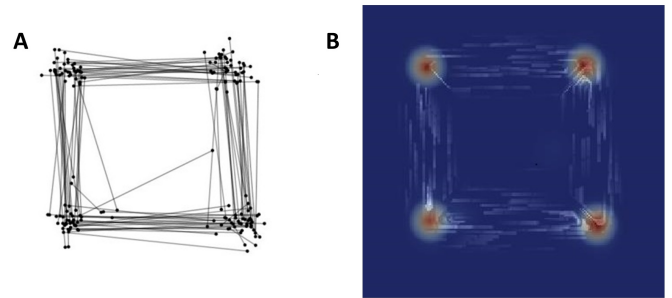


Figure 3: A) Raw data and B) its visualization using visual aggregation technique for the square pattern.

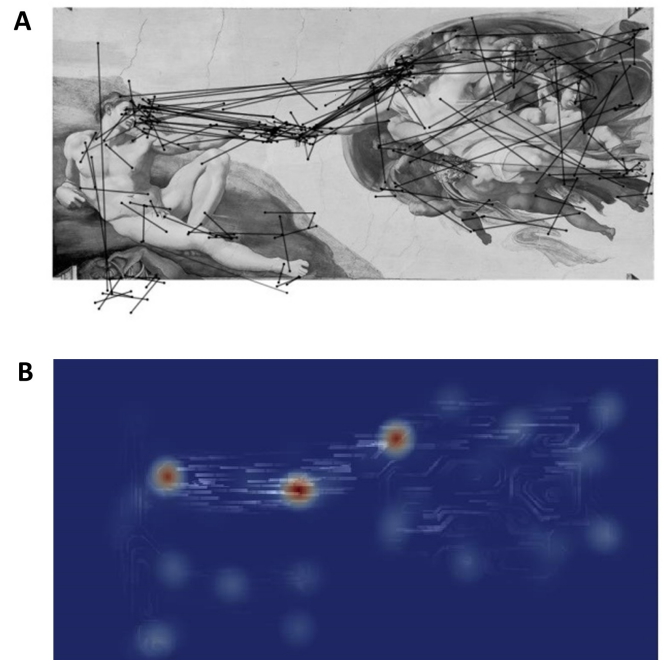
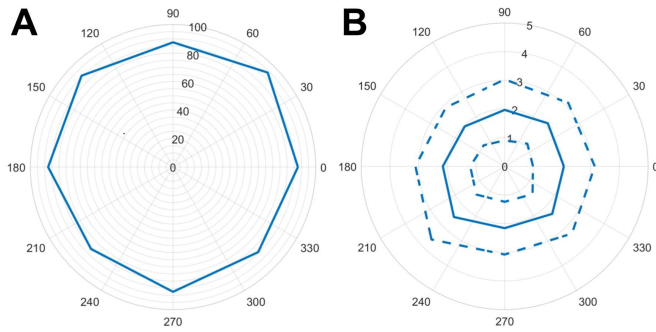


Figure 4: A) Raw data and B) its visualization using visual aggregation technique for the pattern of an observer of the Michelangelo, *The Creation of Adam* [public domain].

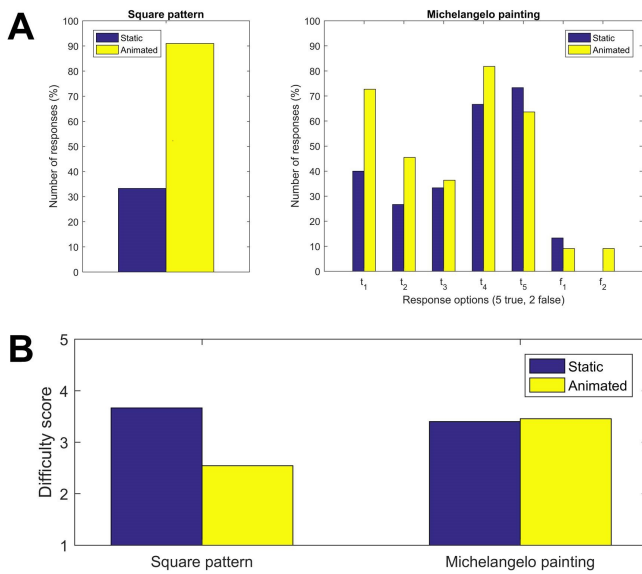
available in open access (See [Peysakhovich and Hurter 2018], Supplementary files). In the static condition, the image corresponded to Fig. 3B and Fig. 4B. In the animated condition, we generated another frame using a larger convolution kernel (see [Cabral and Leedom 1993]). The interval between two frames were set to 200 ms. The answers were depicted with arrows connecting the areas of interest (4 corners for the square patterns, two heads and hands connection for the Michelangelo example).

### 3.3 Results

We describe the results of the survey using only descriptive statistics and presenting the mean values  $\pm$  standard deviation. The claims



**Figure 5: The accuracy (A) and the perceived task difficulty score (B) according the direction.**



**Figure 6: The accuracy (A) and the perceived task difficulty score (B) for square pattern and Michelangelo painting dataset for both static and animated conditions.**

of style "relatively easy" or "relatively hard" are made relatively to the question scale from 1 (very easy) to 5 (very hard).

*Direction perception.* In the first part of the experiment, the participants gave their response in about  $6.3 \pm 2.4$  seconds. The accuracy was  $87.5 \pm 3.7\%$  without any effect of direction. The task was perceived as relatively easy ( $2.2 \pm 1.0$ ). Figure 5 shows the results according to the flow direction.

*Pattern perception.* In the second part of the experiment, the participants gave their response in about  $59.5 \pm 11.5$  seconds.

Figure 6A shows the number of correct responses for the square pattern and the Michelangelo painting dataset for both static and animated conditions. Figure 6A shows the perceived task difficulty.

In the static condition, 33.3% of the participants gave the correct response for the square pattern, considering it relatively hard

( $3.7 \pm 0.7$ ). In the animated condition, 91% of the participants gave the correct response and considered it relatively easy ( $1.3 \pm 2.5$ ).

For the Michelangelo painting, in static condition, participants identified less often the 5 true transitions compared to the animated condition (see Figure 6A). They considered it quite hard in both static ( $3.4 \pm 0.9$ ) and animated condition ( $3.5 \pm 0.8$ ).

## 4 DISCUSSION

### 4.1 Direction and pattern perception

The results of this preliminary study showed that the direction illustrated by OLIC technique can be easily decoded from a picture without any specific instruction nor training. The participants answered the questions with ease (average 2.2 of the difficulty score) and in just about 6 seconds. The majority of the responses were correct (87.5% accuracy), in few cases the directions being taken by the opposites.

These preliminary results could be possibly further improved by considering different parameter settings, i.e. kernel width used for the OLIC computation, or even different visualization method using more complicated glyphs for the vectors [Laidlaw et al. 2005].

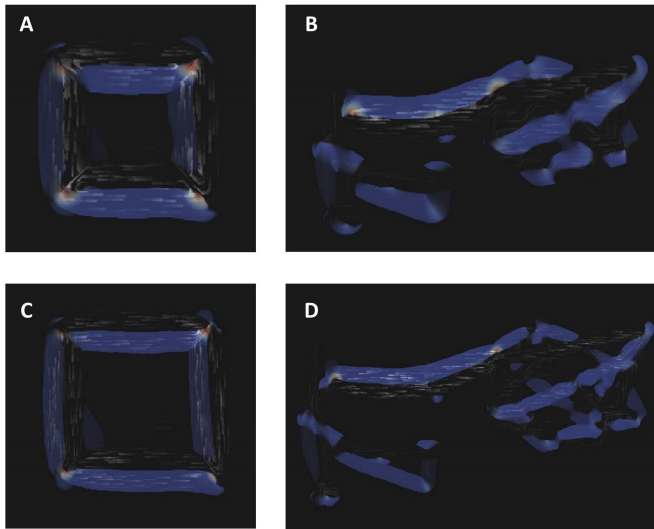
The pattern perception task was more demanding for naive non-expert users that are not used to heat maps nor vector field visualization methods. However, we aimed to understand to what extent such visualizations can be used without any notice nor training. Participants considered this task much more difficult than the first part of the experiment (difficulty scores above 3). They took about a minute to explore each illustration before giving their answer. The general response accuracy was quite low. For example, only one-third of the participants guessed that all 4 pairs of transitions were present on the square scanpath illustration (Figure 3B) in the static condition. However, the animation condition largely enhanced the performance. Thus, 91% of the participants correctly identified all transitions of the square pattern and found it very easy (average difficulty score of 1.3). In case of the Michelangelo piece, the animation improved the accuracy but at a cost of task difficulty. The participants still considered it to be quite demanding (average difficulty score of 3.5).

These results show that in some cases the nature of the eye movements data can be successfully understood from a single static image. It also appears clear from the results, that the animation greatly improves the easiness of the analysis and its performance, which is consistent with the literature [Chevalier et al. 2016]. Therefore, it is preferable to visualize the eye movement data in a small animation since it provides useful insights on the flow direction. However, it is limited to electronic devices screens and cannot be printed on a piece of paper. Hence, there is a need for further research on most efficient methods of intuitive illustrations of the eye movements data in a single static image.

### 4.2 Visual-based improvements

This paper reports evidences of particle-based visualization of gaze direction on a static or dynamic map. While these initial results are interesting, the visual design space of such data representation is far more complex. In this section, we discuss possible improvement to support a more efficient data retrieval.





**Figure 7: Enhancing visualization using lighting: pixels intensities are weighted using the dot product of the local flow direction and the light source vector. Examples of square patterns and Michelangelo painting in normal resolution (A and B) and high resolution (C and D).**

Image-based techniques support fast and accurate data representation thanks to advanced rendering and interactive techniques [Hurter 2015; Scheepens et al. 2016]. Since this work relies on previous image-based visual simplification technique [Peysakhovich et al. 2015], image-based technique smoothly apply. As an example, the computer density maps can be used to display fixation points with a shaded 3D map [Hurter et al. 2012]. One can also take advantage of the computed directional density map to retrieve the flow direction and use a specific color coding to better visually discriminate opposite flow direction. For example, Figure 7 shows the result of a Phong shading using dot product of the flow direction and light source vectors. The use of lighting enhances the reading of the opposite directions.

The investigation of the image-based design space for gaze-based visualization is far beyond the scope of this paper. We rather provide here evidence of visual assets to an image-based technique for this specific data type visualization. Furthermore, image-based technique supports interactions with for instance the fast data filtering and data deformation (i.e. focus plus context technique [Card et al. 1999]). As an example, the MoleView provides can provide filtered information in the center of a lens while showing unfiltered contextual information [Hurter et al. 2011].

## 5 CONCLUSIONS

In this work, we presented a novel visualizing technique that consists of blending the images of the heat map and the visualization of flow direction map for the eye tracking data. We conducted a web-based survey that showed that these visualizations can be successfully used in some cases to analyze the patterns of the eye

movements. The results also showed that the animated representation allows to ease the analyses and improve the performance. These preliminary results could be further improved by using an expanded version of the study and comparing more techniques with novice and expert users. It would be also interesting to evaluate the user's workload while performing the task to quantify different visualizations.

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