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Eye Tracking Data Mining Based on Fuzzy Sets of Fixations

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Abstract. This paper is devoted to the novel method of automated detection of common eye gaze movement patterns by mining the data recorded in eye-tracking-based experiments. For this, a model of aggregated scanpath is proposed that represents a fuzzy set of all possible eye gaze trajectories found in the experimental data. In contrast to the traditional methods of aggregation, no averaging is used to avoid information loss. Instead, the belonging function determines the probability of each particular trajectory. The constructed fuzzy scanpath is then filtered and automatically analyzed by applying methods of network science. For this, the fixations (eye gaze stops) are represented as network nodes and saccades (eye gaze jumps) are mapped to network links. For the network composed, modularity is calculated utilizing the Louvain method of community detection. In the case of eye gaze data, modularity represents saccadic cycles, which can be mapped to the cycles of cognitive processing. Thereby, the common perception structure is retrieved. To support all the analysis steps, we proposed corresponding scalable visualization tools based on our visual analytics platform SciVi. We demonstrate the viability of our approach by analyzing the data obtained from the real-world eye-tracking-based experiment from the Digital Humanities application domain. Preliminary experiment results are discussed along with the efficacy of the proposed methods.

Keywords. Eye Tracking, Aggregated Scanpath, Fuzzy Set, Modularity, Saccadic Cycles, Gaze Movement Patterns, Visual Analytics

1. Introduction

Eye tracking research methodology is widely used to discover information perception peculiarities. It is based on analyzing the eye movement trajectories (also known as scanpaths), which decompose into so-called fixations (moments when the eye gaze is focused on a distinct point) and saccades (rapid jumps of eye gaze between fixations). After more than 100 years long evolution of eye tracking theories, algorithms, software, and hardware, this methodology has grown solid and mature [1]. Nevertheless, when it comes to practical experiments with large numbers of participants, challenges still arise on how to efficiently handle the collected eye tracks, quickly check the hypotheses, and obtain meaningful results [2,3,4].

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Eye tracking data can be classified as Big Data due to their large volume, high sampling velocity, and structural variety [4], which in turn require appropriate data mining tools and machine learning-based methods for efficient and meaningful analysis [5,6]. Traditionally, eye tracks are being analyzed using mathematical statistics [1,2] but recently, the exploratory approach based on visual analytics tends to be an important accompaniment for eye tracking research [7,2,3]. Statistical and exploratory approaches promise a synergy that can increase the value of eye tracking research methodology for various scientific fields, including cognitive science, psychology, medicine, Digital Humanities, etc.

In the present work, we contribute to the development of this synergy by proposing a novel visual data mining approach to analyze the eye tracks leveraged by fuzzy sets of the fixations and modularity of the saccades graph. Thereby we address the challenges of automatic detection of eye movement patterns, scalability of visual analytics tools to a high number of experiment participants (so-called informants), and interactivity of eye tracks spatiotemporal visualizations. These challenges are indicated as belonging to the major ones of state-of-the-art eye tracking research methodology [2]. We implemented the proposed approach within our visual analytics platform SciVi (`https://scivi.tools/`) [8] and tested it in practical use cases within a remit of a research project devoted to studying the peculiarities of multimodal information perception in a virtual reality (VR) environment [9].

The following key contributions of this work can be highlighted:

1. Novel model of an aggregated scanpath of multiple informants based on fuzzy sets of fixations (so-called "fuzzy scanpath").
2. Novel data mining algorithm for revealing the common perception structure of a visual stimulus based on saccades graph modularity within the fuzzy scanpath.
3. Novel interactive visualization tools to display fuzzy scanpath and corresponding graph of saccades.

2. Related Work

Eye tracking data obtained from real-world studies have large volumes and complex structures, which characterize them as Big Data [4]. Thereby, data mining and visual analytics methods are required to efficiently handle them. For example, R. Nava-Martnez et al. successfully utilized Weka, a well-known powerful data mining software, for eye tracking data analysis [5]. The research group that includes M. Burch, T. Blascheck, et al. did a lot of work in applying visual analytics methodology for eye tracking studies starting with a concept published in 2012 [10] and still continuing in 2022 when they presented a very function-rich toolset for the linked and coordinated visual analysis of eye movement data [3]. During their work, this research group also proposed using sequence rule mining and corresponding visual analysis model to detect scanpath patterns [6] and published a very comprehensive survey on visualization of eye tracking data [2]. In this survey, they indicated major challenges of eye tracking as viewed by eye tracking experts. Among other issues, the following are indicated, which are addressed in the present work:

1. "Approaches for automatically detecting patterns are needed".

2. "Visualizations should scale for a high number of participants".
3. "More visualization techniques for eye tracking data are necessary, for example, interactive visualizations or spatiotemporal visualizations".
4. "A way to aggregate and analyze scan paths over a large sample" of informants is required.

Although data mining tasks can often be efficiently tackled by fuzzy systems, the corresponding approaches are underrepresented in eye tracking studies. Only a few authors propose using fuzzy set theory in eye tracking research. For example, D. Zhu et al. propose using fuzzy signatures to detect different eye gaze patterns [11]. T. Opach et al. indicate a possibility to use fuzzy sets for representing areas of interest within the visual stimuli and thereby leveling out the gaze measurement uncertainty [12]. R. A. Naqvi et al. propose a fuzzy system-based approach for improving the eye tracker precision in gaze-based human-computer interaction tasks [13]. In the present work, we apply fuzzy set theory to the scanpath aggregation tasks.

Aggregated scanpaths are traditionally composed as classical sets based on spatial characteristics of fixations and saccades. For example, J. H. Goldberg et al. utilize the so-called "dotplot" method to find sequential matches of scanpaths [14]. V. Peysakhovich et al. propose bundling the saccades and fixations based on geometrical features "to reduce visual clutter" by scanpath rendering "and provide a mathematical base for scanpath comparison" [15]. To the best of our knowledge, no published works address the usage of fuzzy sets for scanpath aggregation.

One of the possible ways to automatically detect eye gaze patterns is fixations and saccades clustering. A. Belardinelli et al. propose a comprehensive mathematical model to estimate fixations neighborhood based on spatiotemporal characteristics and visual saliency of the stimulus in fixations' points [16]. Based on this neighborhood, so-called "saccadic cycles" are retrieved, which represent the cycles of cognitive processing. This method requires no apriori information about the areas of interest (AOIs), which is an advantage in the case of collecting gaze data in natural environments. But this method works on the individual scanpaths of informants, without aggregation. So, for the experiments with predefined semantic AOIs and a large sample of informants, other techniques should be adopted.

Another promising direction of eye gaze patterns detection is "applying network science to eye-movement data" [17]. M. Zhu et al. proposed calculating different network metrics (density, centrality, and clustering measures) for the graph of saccades [18]. Later, this approach was further elaborated by X. Ma et al. [17]. In our work, we take the next step in this direction proposing the approach to retrieving saccadic cycles based on saccades graph modularity calculated for the aggregated scanpath of multiple informants.

There are a lot of community-driven software products designed for eye tracking data analysis (including detection of fixations and saccades, calculating statistical metrics of eye gaze tracks, measuring eye pupil diameter, etc.) [19,20], as well as different tools which help in preprocessing the eye tracking data (for example, an open-source tool for determining the dynamic AOIs created by L. Bonikowski et al. [21]). The novel fuzzy set-based model of representing aggregated scanpaths and the corresponding novel data mining algorithm for revealing common perception patterns proposed in the current paper can be integrated into these software tools in the future. But recently we implemented them within our own software platform SciVi, which distinctive feature is easy extensibility and flexible high-level graphical user interface for declaring data mining pipelines. The distinctiveness of this platform and its working principles are described in detail in [8].

3. Aggregated Scanpath Model Based on Fuzzy Sets

Traditionally, the eye tracking data aggregation challenge (see item (4) in the list of challenges mentioned in Section 2) is addressed by some kind of data merging, for example, by averaging [17] or intersecting [14] of scanpaths. However, in these cases, some information gets lost. To tackle this problem, we propose a fuzzy set-based model of an aggregated scanpath that bundles all the data sampled from the informants during the particular eye tracking experiment. For a sake of brevity, let us call it a "fuzzy scanpath".

Our implementation of fuzzy scanpath and explanation of the related math can be found in the SciVi platform repository: https://github.com/scivi-tools/scivi.web/tree/master/lib/eye/fuzzyScanpath.

Let $A = \{\alpha_j | j = \overline{1,m}\}$ be a set of m predefined AOIs in a visual stimulus. Let $S = \{\sigma_k | k = \overline{1,p}\}$ be a set of scanpaths recorded for p informants during the experiment. Let the scanpath be a set of fixations, each one belonging to a particular AOI: $\sigma_k = \{\varphi_l^{(k)} | l = \overline{1,r^{(k)}}\}$, $\forall \varphi_l^{(k)} : \exists j | \varphi_l^{(k)} \in \alpha_j$. Let $n = \max\{r^{(k)}\}$ be a maximal scanpath length in S. Then the fuzzy scanpath is defined as:

$$T = \bigcup_{i=1}^{n} \bigcup_{j=1}^{m} \left(\alpha_j, \omega_j^{(i)}\right), \tag{1}$$

where $\omega_j^{(i)}$ is a fuzzy set's belonging function representing the number of informants who have their i-th fixation in the j-th AOI:

$$\omega_j^{(i)} = \frac{\sum_{k=1}^{p} \begin{cases} 1, & \exists \varphi_i^{(k)} \vee \varphi_i^{(k)} \in \alpha_j \\ 0, & \text{otherwise} \end{cases}}{p}. \tag{2}$$

The fuzzy scanpath T is a sequence of fuzzy sets, which contains all possible eye gaze trajectories from the experimental raw data. The rationale behind the belonging function (2) is that it represents the "popularity" of each AOI in terms of informants' attention at each fixation. This, in turn, allows checking, which AOI attracts more attention at a given moment of time thereby estimating different variants of eye gaze trajectory and revealing the branches, which are more/less common for the informants' sample in question. Each informant has an equal contribution and no information gets lost.

We implemented the assembling of fuzzy scanpaths as a specific data mining step (so-called "operator") in the SciVi visual analytics platform [8]. This platform has a microservice architecture, so each operator is represented as an individual microservice and SciVi can be easily extended with the new data mining capabilities on demand. To compose a particular data mining pipeline, available operators are chained together using a special built-in high-level graphical programming language based on data flow diagrams (DFDs). A screenshot of the eye gaze data mining algorithm used in this work is presented as a SciVi DFD in Fig. 1. A brief live demo of SciVi functioning is available at https://youtu.be/ItMFmdL1GHY.

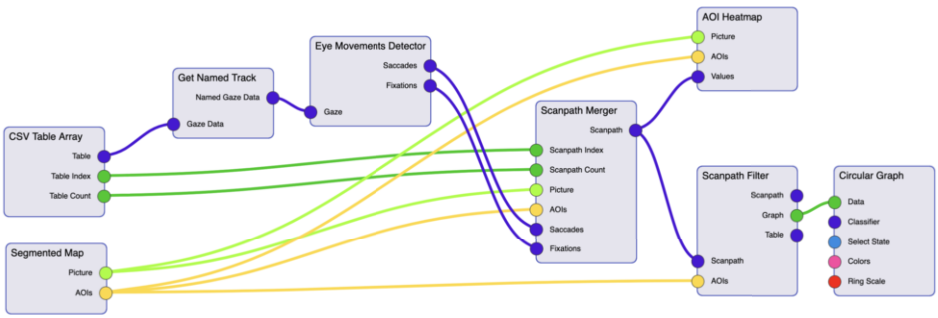

Figure 1. Eye tracking data mining algorithm programmed in SciVi as a data flow diagram.

The “CSV Table Array” operator loads the raw eye tracking data for all informants. These data get filtered by the “Get Named Track” operator to extract the entries belonging to a particular visual stimulus (there are multiple stimuli in our experiment, presented to informants one by one). The “Eye Movement Detector” operator detects saccades and fixations in the set of eye gaze location samples. For this, an algorithm suggested by J. Llanes-Jurado et al. is used [22]. The “Segmented Map” operator loads the descriptions of AOIs for the visual stimulus in question (the segmentation into AOIs is done in the Creative Maps Studio vector graphics editor as described in [9]). The “Scanpath Merger” operator assembles the fuzzy scanpath according to equations (1) and (2). The “AOI Heatmap” operator is used to visualize the fuzzy scanpath as an interactive heatmap. The visualization result is presented in Fig. 2.

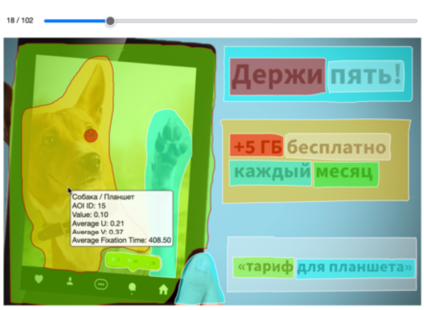

Figure 2. Fuzzy scanpath visualization as interactive heatmap in SciVi (interactive view available online https://scivi.tools/demo/fuzzyScanpath).

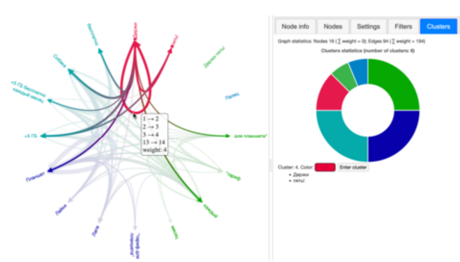

Figure 3. Saccades graph and its modularity visualization in SciVi (interactive view available online https://scivi.tools/demo/saccadicCycles).

The slider on the top allows choosing the fixation. The heatmap represents the values of $\omega_j^{(i)}$ for the chosen fixation. The percentage on top of the color scale represents the ratio of informants who have the chosen fixation. Mouse hover triggers the tooltip with context information about AOIs: name and identifier of AOI, value of $\omega_j^{(i)}$ for this AOI, average fixation time, and average fixation coordinates (called U and V, as they are normalized in image space; at this point, the red circle is drawn for the hovered AOI; the radius of this circle is proportional to the average fixation time). This visualization helps the analyst to explore the fuzzy scanpath and discover its peculiarities.

4. Retrieval of Common Perception Structure

We propose using the fuzzy scanpath to automatically detect eye movement patterns addressing challenge (1) from the list of challenges mentioned in Section 2. We follow the assumption of A. Belardinelli et al. that "... saccades and fixations can be clustered, considering them related to a single cycle of cognitive processing" [16], combining this idea of clustering with the idea of M. Zhu et al. and X. Ma et al. on using a network representation of saccades and fixations [18,17]. Fixations and saccades are mapped to the network's nodes and links, respectively, and network science methods are applied to analyze this network. In particular, we propose retrieving the saccadic cycles (described by A. Belardinelli et al. [16]) by using the Louvain method for community detection [23]. This method calculates the graph modularity by finding so-called "cliques" – graph components of high connectivity. In the case of the saccades graph, modularity can be interpreted as the saccadic cycles. Since the saccades graph is built on top of the aggregated scanpath, the retrieved saccadic cycles reveal the common perception structure of the informants.

In the case of a large sample of informants, threshold filtering of the fuzzy scanpath is reasonable to extract the mainstream eye gaze trajectory. This can be done by rejecting all the outlier elements of T (see equation (1)), which do not meet the following condition for each i-th fixation:

$$\omega_j^{(i)} \geq \max\{\omega_j^{(i)}\} - \tau \vee \vartheta^{(i)} > \theta, j = \overline{1,m}, \tag{3}$$

$$\vartheta^{(i)} = \frac{\sum_{k=1}^{p} \begin{cases} 1, & \exists \varphi_i^{(k)} \\ 0, & \text{otherwise} \end{cases}}{p}, \tag{4}$$

where τ and θ are given threshold values, p is a number of informants, $\varphi_i^{(k)}$ is a fixation of k-th informant.

In the pipeline shown in Fig. 1, the "Scanpath Filter" operator performs this filtering. After that, the "Circular Graph" operator visualizes the saccades graph. This operator provides a rich toolset for comprehensive analytics of graphs, including the calculation of modularity based on the Louvain method [24]. The visualization result is shown in Fig. 3 (in this example, $\tau = 0.03$, $\theta = 0.33$, $p = 41$). The nodes of the graph represent fixations in the AOIs; the edges represent the bundled saccades. The edge thickness represents the number of saccades in a bundle. The saccadic cycles are color-coded and their size is reflected by a pie chart on the right. Mouse hover on the edge triggers a tooltip showing individual saccades in a bundle, ordered chronologically.

5. Discussion and Conclusion

We applied the proposed data mining algorithm to analyze the eye tracking data recorded in the following experiment (see the schema in Fig. 4). 14 visual stimuli were demonstrated to 41 informants (sample balanced by age and gender) in VR. The visual stimuli were the posters with an image and a short text (taken from the different commercial advertisements and normalized to look uniformly) [25]. 7 posters presented a story with a single interpretation and 7 had an ambiguous sense. Each "ambiguous" poster presents some idiomatic expression that is represented in a text and is supported by a picture, whereby its literal meaning is used in an advertising context. One of the "ambiguous" posters is shown in Fig. 2 overlaid with a gaze heatmap. In this poster, there is a slogan "High five!", followed by an explanation "+5 Gb free each month" and "tablet plan" (advertising a service of a mobile telecommunications provider). The picture shows a dog with a raised paw inside a tablet frame.

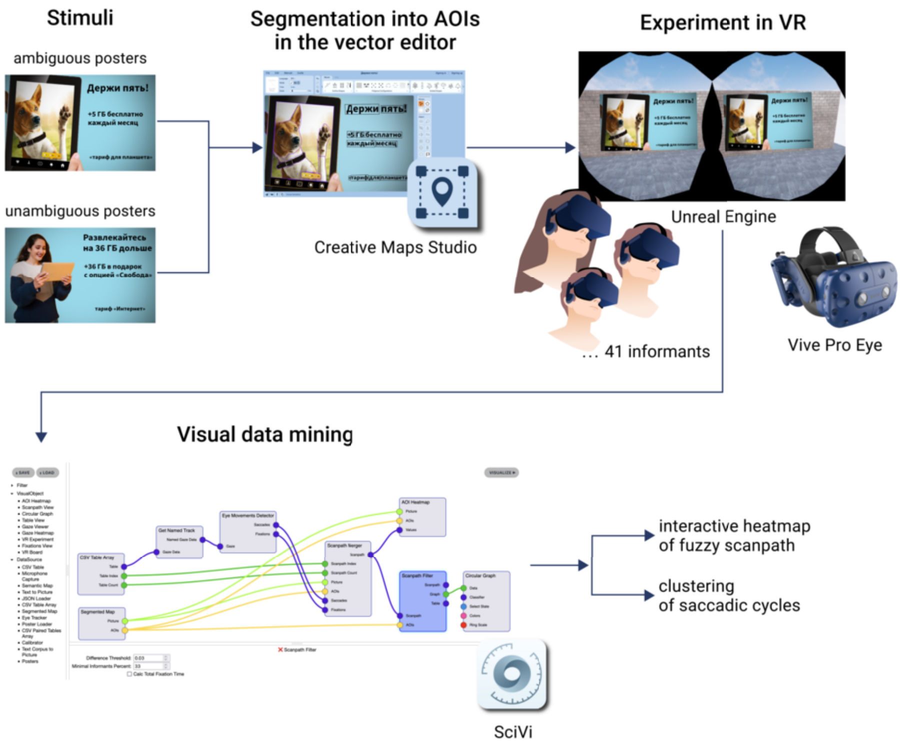

Figure 4. Schema of the experiment conducted.

The posters were shown one by one in a VR environment rendered by the Unreal Engine and demonstrated to the informants via the Vive Pro Eye VR station. The informants' eye gaze tracks were recorded by an embedded Tobii eye tracker. Each poster was manually segmented into AOIs in the Creative Maps Studio vector editor [9]. Then, the experimental data were analyzed in the SciVi platform using the data mining algorithm shown in Fig. 1. The average processing time of this data mining algorithm for the single poster (41 eye gaze tracks; 42324 eye gaze samples in total) is 538 ms (on a MacBook Pro, 2.3 GHz 8-Core Intel Core i9 CPU, 16 Gb RAM), which is nearly a real-time speed in terms of fine-tuning the data mining parameters and checking hypotheses about the data.

The following preliminary results were obtained by exploratory and statistical analysis of the fuzzy scanpath constructed from the collected data (see Fig. 2 and Fig. 3 which represent the visualizations related to the analysis of fuzzy scanpath and saccadic cycles for the single poster). The gaze trajectory follows the general pattern: "the text viewed first, then the image". It seems, that informants are able to catch the ambiguity from the text by the first 3 fixations, and then start searching for the explanation of ambiguity in the image. While the reading time for "ambiguous" and "unambiguous" posters is approximately equal, image inspection time for "ambiguous" posters is significantly longer, including more saccadic cycles. As a result, the total dwell time for "ambiguous" posters is longer. Saccadic cycles reveal groups of AOIs. For "unambiguous" posters, these groups are rather morphological (text and image are separated into different groups), and for "ambiguous" posters, groups are semantical (text and image are mixed; semantically connected parts of text and image are grouped).

In the example of an "ambiguous" poster analysis shown in Fig. 3, the following saccadic cycles have been found through the graph modularity:

1. "tablet", "plan", "each", "month".
2. "tablet plan", tablet picture, dog's paw picture, picture with likes on a tablet.
3. "+5 Gb", "free", "+5 Gb free each month", dog picture.
4. "High", "five!".

These saccadic cycles (especially (2) and (3)) clearly show the process of comprehension whereby the informants reveal the story represented by a poster.

We can state that these preliminary results prove the viability and efficacy of the approach proposed.

The proposed fuzzy scanpath model, data mining algorithm built on top of that model, and corresponding visualization tools address altogether the 4 challenges mentioned in Section 2. The developed software solution allows for aggregating the scanpaths over the large sample of informants, automatic detection of their common eye gaze movement patterns, and provides scalable interactive spatiotemporal visualization via heatmaps and graphs. This software solution is open source and freely available on GitHub under GPL3 license: `https://github.com/scivi-tools/scivi.web`.

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