

Supporting Exploration of Eye Tracking Data: Identifying Changing Behaviour Over Long Durations

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ABSTRACT

Visual analytics of eye tracking data is a common tool for evaluation studies across diverse fields. In this position paper we propose a novel user-driven interactive data exploration tool for understanding the characteristics of eye gaze movements and the changes in these behaviours over time. Eye tracking experiments generate multidimensional scan path data with sequential information. Many mathematical methods in the past have analysed one or a few of the attributes of the scan path data and derived attributes such as Area of Interest (AoI), statistical measures, geometry, domain specific features etc. In our work we are interested in visual analytics of one of the derived attributes of sequential data—the AoI and the sequences of visits to these AoIs over time. In the case of static stimuli, such as images, or dynamic stimuli, like videos, having predefined or fixed AoIs is not an efficient way of analysing scan path patterns. The AoI of a user over a stimulus may evolve over time and hence determining the AoIs dynamically through temporal clustering could be a better method for analysing the eye gaze patterns. In this work we primarily focus on the challenges in analysis and visualization of the temporal evolution of AoIs. This paper discusses the existing methods, their shortcomings and scope for improvement by adopting visual analytics methods for event-based temporal data to the analysis of eye tracking data.

CCS Concepts

•Human-centered computing → Visualization techniques; Visualization design and evaluation methods;

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Keywords

Eye tracking, pattern analysis, scan path, time evolving AoIs, Clustering of Fixations, ActiviTree

1. INTRODUCTION

Eye tracking is a technology which has become increasingly popular over the last 15 years as the associated hardware has improved and its cost has dramatically reduced. While still not inexpensive, and so hardly ubiquitous, eye-tracking is being used by many groups to perform experimental studies in visualization and user interface design as well as film, advertising and related fields [12, 3, 4]. Once correctly calibrated, the eye tracking equipment samples the eye position and orientation within a working volume at a rate typically in excess of 100Hz, often much higher, to determine the gaze direction and so the gaze point on the screen. From this information, for example, the parts of the display which are of greatest interest to the viewer can be determined due to the number and duration of fixations (periods of gaze) as well as the movements (saccades) between fixations as the viewer switches their gaze point. For a visual data analysis task this can enable the experimenter to directly determine those parts of the visual information display which the analyst finds most valuable and interesting, the parts of the user interface which are used most frequently, or those functions which are most difficult to locate, and to examine the sequence of actions which the analyst makes when carrying out a task.

The data retrieved from the eye-tracking device is generally in the form of fixations, filtered from the raw gaze-point data, accompanied by screen position, time-stamps, duration, a sequence number, and a plethora of other information. This data can then be analysed in many ways, according to the experimenters needs, but most common is to examine areas of interests (AoIs) for the test subject through representations such as heat maps [4], which may be shown for some time window within the data, and animated displays of the sequence of fixations as a scatter plot and the associated saccades using lines or arrows. These displays can be very effective for relatively short tracking experiments, perhaps lasting a few minutes, and so are routinely used for many experiments in visualization, but they can become extremely problematic when longer studies are being carried out with each session lasting, perhaps, a few hours. In such instances these simple displays can become extremely cluttered making the analysis of the eye-tracking data a very laborious and time-consuming task even when specific events are being explored within the data and mak-

ing a purely exploratory analysis of the data close to impossible. The authors have recently become involved in experimental work being conducted by colleagues within the field of air traffic control [32]. Their experimental tasks typically require eye-tracking studies lasting as long as three hours per session, and they are particularly interested in changes in the behaviour of the test subjects, the air traffic controller, due to events in the (usually simulated) airspace which they are monitoring. Some of these events can be predicted or deliberately inserted into the simulation, permitting the experimenter to focus on particular short segments of the eye-tracking data, but there is a need to be able to perform an exploratory analysis of the full duration data to identify unexpected changes in behaviour by the controller. To date this analysis has proven too time-consuming to perform, with one three hour experimental study session requiring more than a week to analyse using purely visual means.

The analysis which is desired within these longer studies is to identify the AoIs across the display from the eye-tracking data itself, to identify how these AoIs shift as the task progresses and events occur, to then find patterns of behaviour of the test subjects and to identify how those patterns of behaviour change over time. These AoIs and the changes over time can then be compared between subjects and similarities and differences in their response can be identified and the reasons behind those differences explored. Identification of AoIs over time and displaying them, while retaining their sequential and relational information, is then a significant problem in the data analysis due to the extensive clutter which can be expected. This problem is further compounded when the study involves comparison between multiple test subjects. To this end, and inspired by previous work in the field of activity data for populations [35], we have begun applying and developing automated and interactive methods to assist in analysing these long time sequences to identify both consistent and shifting AoIs within the recorded eye-tracking data for one subject, sequences of visitations to these different AoIs for a single test subject and changes in that subjects behaviour over time. Having enabled the experimenter to identify such behaviour, and so changes of behaviour over the lengthy duration of the experimental study, we can then produce comparison plots for multiple test subjects to complete the exploratory analysis required for the experimental study. We now review some previous related work and then describe some of our first research directions and ideas for future work in this area. The proposed visualization approach will thus work towards,

- Using clustering methods such as mean shift clustering for identification of temporally evolving AoIs.
- User-driven exploration of temporal AoI sequences collected from multiple users and visualizing their sequential and relational information in an intuitive manner without visual clutter.

2. ANALYTICS BASED ON AOI

Raw eye tracking data is in the form of gaze coordinates and duration. Typical commercial software such as Tobii Studio [1] convert it into scan paths made of fixations and saccades. Following on from a study of the various data formats used across many eye tracking systems [36] a recent

paper by Winkler et al. [37] standardized a list of attributes for eye tracking data and the need to do the same across future datasets. The sequential part of the eye tracking data is usually stored in the form of scan paths containing attributes such as (1) fixation information like sequence, position and duration (2) saccadic information like position, length, amplitude and direction. The existing canon of methods dealing with analytics of eye tracking data either operate on the sequential scan path information or on certain derived attributes from them such as (1) AoIs, (2) geometric information such as circular, linear or mixed patterns, (3) application specific feature vectors such as median x, y position of eye fixations etc. The data becomes multidimensional when multiple scan paths are collected from different input stimuli (dynamic or static), from multiple users, or from multiple iterations etc. A recent state of the art report on visualization methods for eye tracking data [4] classifies AoI based visualizations into Timeline AoI representations and Relational AoI representations. Timeline representations (AoI sequence charts, scarf plots, AoI rivers, parallel scan path visualizations etc.) and Relational AoI representations (AoI trees, graphs etc.) do not scale well to a large number of AoIs, or to multiple users. Visual analytics of AoIs can be broadly classified into two categories,

- methods that deal with static predefined AoIs
- those that treat AoIs as time evolving entities in static or dynamic stimuli

2.1 Static AoI-based analytics

The stimulus is divided into predefined AoIs and transitions between these different AoIs are analyzed for gaze patterns. The disadvantage of predefined static AoI definition is that it can fail to capture the temporal evolution of the user's attention over time, particularly when long duration experiments are involved. A stimulus can contain a large number of AoIs that increase over time and over multiple user trials. Identifying them in an efficient way, and studying their temporal evolution, has its advantages.

Transition matrix. Transitions between the AoIs are modelled as transition matrices in a tabular form representing the number of transitions to and from each AoI. If the matrix is dense with most of the cells containing transition information, it indicates an extensive search on a display while sparse matrices indicate more efficient and directed search. While the frequency of particular transitions between AoIs is shown, such matrix representations do not convey the temporal aspects of the user behaviour well since the ordering of the transitions is not easy to represent.

Markov models. Transitions between different AoIs can be modelled as first order Markov chains [30] where the transition to a future AoI is dependent only on the present AoI and not on the past AoIs. The Shannon entropy coefficient of the Markov model is then computed to quantify the transition across AoIs. While initial methods presented in [19] were restricted in the number of AoIs due to the error associated with sparse transition matrices, methods like [18] extended the above approach to multiple AoIs and stimuli-independent subdivisions of AoIs. Transition entropy is used to understand the scanning patterns of subjects, with higher entropy indicating more randomness in the sequence of visits of AoIs, while a smaller transition entropy value suggests dependencies between two successive AoI visits. Station-

ary entropy presents us the distribution of attention among AoIs, with higher entropy indication that there is a uniform distribution of visual attention among AoIs, while a smaller stationary entropy suggests eye fixations are concentrated on specific AoIs as they attract more visual attention.

Reinforcement learning algorithms. While the transition matrices and Markov models estimate the conditional probability of scan paths only to the first order i.e, only between two AoIs, thereby looking at only one step of the sequence, while higher order matrices suffer from less data (transitions) to calculate an accurate estimate and hence limiting the number of AoIs in a stimulus. Reinforcement learning algorithms learn to predict future scan paths based on past scan paths [13]. Once a transition happens from one AoI to another, instead of simply updating the transition probability from the first to the second AoI, the method associates the first AoI with the second AoI and all expected subsequent AoIs based on prior visits to the second AoI.

Scanpath comparison methods. AoIs are assigned symbol strings and methods such as String edit distance analysis [7] and MultiMatch [10] are used to compare two scan paths but they are constrained in searching for patterns within scan paths. Finding repeated patterns inside a scan path suffers from quantization error due to the fixed sized window constraint that breaks the approximated string representation of the scan path for comparison [20]. Only a loosely coupled grammar can be derived for finding the patterns from the string representation. [2] provides a state of the art report on different scan path comparison methods. Several visualization methods such as circular heat maps [6], AoI rivers [8] etc., have been used to display the AoIs from static stimuli featuring fixation count inside AoIs, transitions between AoIs etc.

2.2 Temporal evolution of AoIs

Due to the evolving nature of AoIs over time, visual analytics of gaze patterns in dynamic stimuli, such as videos, is a complex task [23]. Static stimuli are not an exception since new users seeing a stimulus for the first time may find different areas of the display to be interesting and, once they gain an understanding, the AoIs in their gaze pattern may change altogether [22]. Similarly a complex visual data analysis task may involve several steps, each making use of different parts of the display which will be reflected in different AoIs during difference phases of the analysis. Annotation of AoIs may be based on fixation counts on a local neighbourhood, the number of transitions between two regions in the stimuli represented and analysed using transition matrices [15]. The first step in the visual analytics of spatio-temporal AoIs is clustering them by taking the temporal aspect into account and the next step is visualizing them using methods that portray their sequential nature, duration of occurrence over multiple users and iterations.

Clustering methods. Hierarchical methods, density-based and grid-based methods are some of the clustering techniques that have been used to group fixations into AoIs. A comprehensive list of clustering methods can be found in [14, 17]. Several similarity metrics have been used to cluster fixations in [24] such as Levenshtein distance, attention distribution-based and AoI transition-based methods. Multilevel visual groups based on agglomerative hierarchical clustering [17] were created on the dynamic targets in the scene [15] where they take into account the inherent hierar-

chical structure present in the AoIs of gaze patterns. Some of the clustering methods relevant in the context of large data are explained in Section 3.1.

Visualization methods. Visual exploration of clustering results can be performed using numerous visualization techniques. The Space-Time Cube (STC) has been used to display the time evolving nature of regions of interest, their temporal duration, underlying stimuli (dynamic/static) and aggregated information from multiple users [25, 11]. The spatio-temporal context of AoIs across multiple users, stimuli and iterations can be represented in STCs but simultaneous display of all AoIs leads to visual clutter. Later methods have used a combination of synchronized views to overcome this problem. ISeeCube identifies time evolving clusters of fixations using mean shift clustering and displays them in STC visualization. AoIs are annotated manually based on the identified clusters and displayed using STC and the visual clutter is handled through synchronized scarfplots and timeline views [24]. Among alternative visualizations that try to reduce visual clutter, scarfplots are an efficient way of representing AoIs and their evolution over time, but they still suffer from colour coding, clutter over time and multiple user trials. Hence hierarchical visualization approaches that take into account the inherent hierarchies in AoI clusters over time are used in [5]. In this recent work multiple visualization tools such as AoI trees, graphs, transition matrix and hierarchy diagrams have been used to collectively portray the sequential, relational and temporally evolving nature of AoIs. The AoI Transition Trees approach [26] combines scarfplot with an additional space-filling icicle plot diagram that provides a hierarchy of transition sequences. Thumbnails that represent the AoIs from the stimuli are added to the nodes of the tree. The height of the thumbnail corresponds to the frequency of visits to that AoI. It focuses on the strategy of how AoIs are visited rather than what AoIs were visited. They perform clustering and identification of AoIs through the ISeeCube interface. eSeeTrack [34] uses a similar visualization structure but, in place of thumbnails, words were used as tree nodes that were similar to that of WordTree. The purely visual representations described above can suffer from visual clutter, particularly when dealing with long duration data. While AoI trees, graphs, scarfplots etc. suffer from the same big data problem, transition matrices cannot convey the time evolving nature of the AoIs. In AoI trees, for example, the arrows depicting transitions between AoIs can become cluttered over time. In order to overcome this shortcoming, we propose a semi-automatic user driven approach for interactive exploration of AoI sequences over time. In this paper, we plan to adapt algorithms used for exploring sequences in a large event-based data collected from multiple users [35]. A tree inspired clutter free representation is used to explore paths of AoI nodes one at a time chosen by the user and a scarfplot like representation to highlight the AoI across time, duration and multiple users (Refer to Figure 2).

3. INTERACTIVE VISUALIZATION OF TEMPORAL EVOLUTION OF AOI

The first step of our approach is to use fast clustering algorithms such as the mean shift method that can identify temporally evolving AoIs in both static and dynamic stimuli. In the second step, the visual clutter due to over-

plotting in the timeline AoI displays will be addressed using a novel approach. It is new to this field with its origins from algorithms and techniques used for interactive exploration of event-based datasets - the ActiviTree method [35]. Using this approach, users can analyse how the transition between AoI sequences have evolved over time and identify AoI sequence paths followed by different users based on their significance determined by the data analyst.

3.1 Identification of AoIs through clustering

Automatic clustering reduces the time consuming manual AoI definition that requires prior knowledge from the analyst. When dealing with raw data, identification of fixations, saccades and smooth pursuits (dynamic stimuli) can be carried out effectively using probabilistic models. Online methods such as Bayesian model based clustering algorithms [33] can be used. The advantage of using probabilistic methods over threshold based systems is that they are parameter free and are not limited by thresholds, rather they learn them from the data itself [16]. When huge volumes of eye tracking data that do not fit in the main memory are to be involved in the clustering process, density-based clustering methods based on DBSCAN can be used [28]. As our aim is to find temporally changing AoIs, threshold based algorithms that expect input parameters in advance in the form of number of AoIs etc. are not suitable. For clustering the fixations, we initially plan to use the mean shift clustering method [9, 31] that has inherent advantages in finding AoIs that evolve over time and the identification of them is not through an analyst but data driven [11]. The raw eye tracking data is collected in the form of screen position and time stamp $D_i = (x_i, y_i, t_i)$. Mean shift clustering iteratively moves points to locations of higher density called *modes* - the weighted mean of neighboring points based on a multivariate gaussian kernel. A scale parameter σ is used to specify the kernel, increasing its value results in fewer, larger clusters. This parameter does not control the actual size of the density cluster, but it makes sure that no two clusters exist which are closer than this scale parameter. Optimum values for this scale parameter can be determined automatically using methods described in [31, 27]. The algorithm computes clusters of interest that are robust to noise and small outliers. The method is very effective over traditional methods and is used in the Eyetrace software tool [21]. Irrespective of any methods, while performing clustering for identification of AoIs in a stimulus for multiple users, the clusters should be in sync with the other users also. Coherence should be established across clusters discovered across time and different users. In this process, user specified threshold values can account for inherent noise in treating two different clusters as a single cluster. Mean shift method can clearly perform robust clustering on data from different users in the presence of noise producing coherent AoIs [31]. The location property of the clusters, such as the centroid, can be used to establish this coherence across different viewers, time periods etc based on a predefined threshold.

3.2 Methodology behind clustering

While clustering the fixation points into AoIs, the emphasis lies on identification of AoIs based on the geometrical position of the occurrence of fixations across any kind of stimulus: static or dynamic - active or passive. We consider the AoI identification across different users and stimuli purely

from a geometrical perspective of the neighboring fixation positions and thereby avoid the process of associating the underlying semantic information of the stimulus with the identified AoIs and the necessity to make the identification of AoIs in sync across different types of stimuli.

Once the data analyst identifies an interesting sequence of AoIs visited by different users, the semantic information of the stimulus that stimulated an Area of Interest for the user can be highlighted on the underlying stimulus in a separate co-ordinated view. In this subsequent step, the nature of the stimulus being static or dynamic - active or passive that simulated this aggregation of fixation points at a particular region can be analyzed. While this step does not necessitate the AoI identification process to be in sync with the underlying stimulus, it should be understood that it is not the same with regard to geometric position of occurrence of AoIs. When the identification of AoIs is performed across different users, there is a necessity for uniform labelling of AoIs based on their position of occurrence in the stimulus. Hence the identified AoIs should be in sync across different users purely from the perspective of the geometrical position of AoIs.

3.3 ActiviTree for exploring temporal evolution of AoIs

ActiviTree [35] was developed for exploring sequences in event-based temporal data collected across large numbers of test subjects. The exploration is user-driven and it overcomes the disadvantages of visual clutter in the space-time cube: AoI trees and graphs of increasing size [35]. In this context the event data is related to sequences of visits to the AoIs within the eye tracking data as they share sequence information and duration across multiple users. We can adopt this approach for the analysis of temporally evolving AoIs in an eye tracking data set collected across different users.

ActiviTree for AoI sequence data. Figure 1 illustrates a snapshot of the ActiviTree visualization framework applied on social science diary (event) data over long durations. The visualization is divided into two views - the ActiviTree visual interface and a linked view containing the event sequences with time of occurrence of events mapped against the vertical axis and the data collected from different users mapped against the horizontal axis. In our proposed framework, we can adapt this visualization model wherein the event sequences are replaced with AoIs from eye tracking data. The view containing AoI sequences resembles that of a Scarfplot [29] and the use of the ActiviTree interface not only reduces the visual clutter but also handles the inability of Scarfplots to portray transition information between AoIs. It is a hybrid approach making use of a Timeline AoI and a Relational AoI representation in an interactive and efficient manner. It is more intuitive when compared with AoI trees and graphs where filtering options and thresholding were used to reduce visual clutter. Also the interface can be used to compare eye tracking data collected from different stimuli or users or iterations. Methods such as transition diagrams and recurrence quantification can be employed to convey the high frequency and recurrent patterns in eye gaze data and so guide the user in selecting potential AoIs of interest in the sequence. While in these methods, the term frequency of a certain pattern is synonymous with interestingness in a eye tracking data, ActiviTree enables an analyst to drive the data exploration process to find patterns based on their

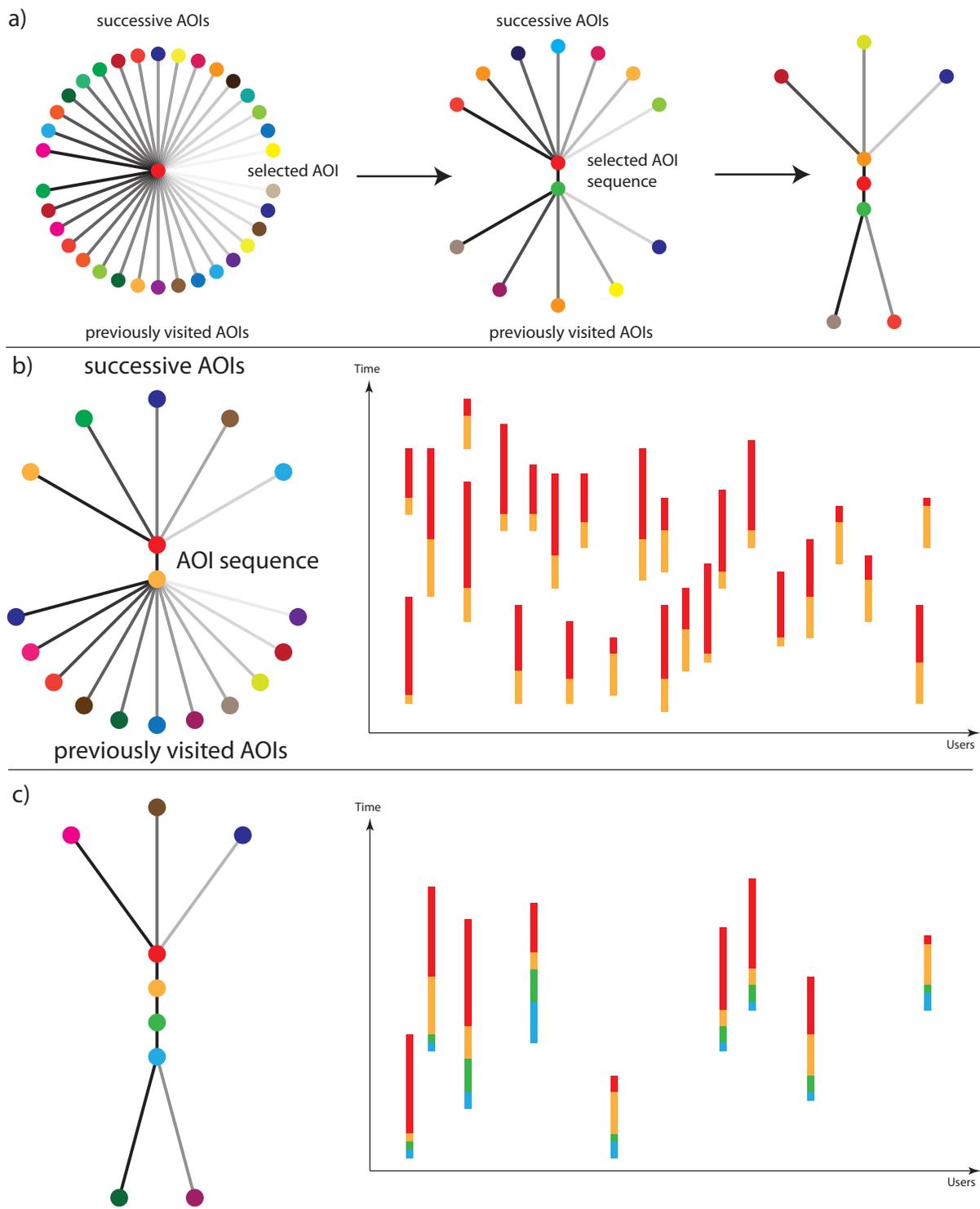


Figure 2: Methodology of ActiviTree based visual interface. a) At the initial step, users are free to select a single AoI based on their significance score computed across different users. All the previously visited AoIs and successive AoIs for the selected AoI is represented in a tree diagram. Tree nodes represent the AoIs computed from the clustering step and they are arranged in their increasing order of significance from right to left. Data analysts trying to find interesting AoI sequences can interactively select a subsequent AoI and construct an AoI sequence path. The sequence of AoI visits along with their duration and temporal information are displayed in a scarfplot like sequence plot to the right as shown in b) and c).

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