Multi-Similarity Matrices of Eye Movement Data

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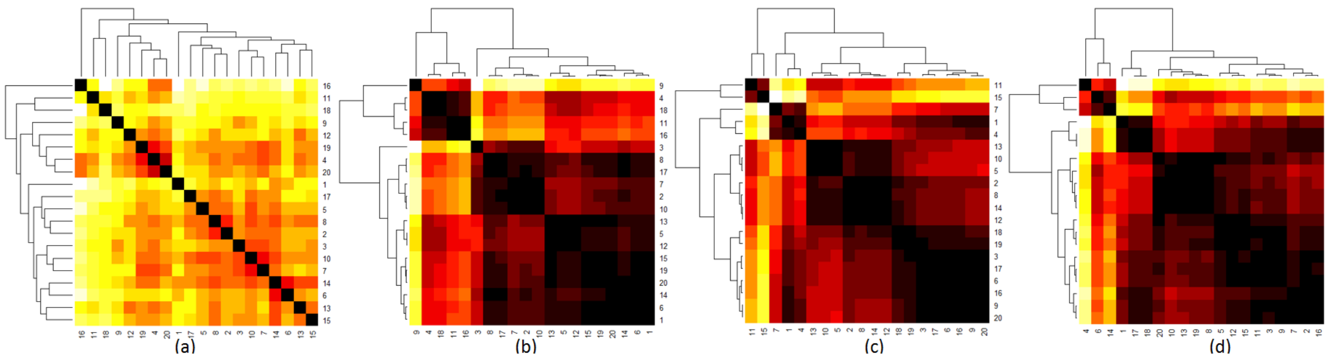

Figure 1: Eye movement metrics visualized by a clustered matrix along with a dendrogram that shows the structure of the hierarchical clustering: (a) metric M_1 (path transition), (b) metric M_2 (fixation duration), (c) metric M_3 (saccade length), and (d) metric M_4 (completion time).

Abstract

We describe a matrix-based visualization technique for algorithmically and visually comparing metrics in eye movement data. To reach this goal, a set of scanpath trajectories is first preprocessed and transformed into a set of metrics describing commonalities and differences of eye movement trajectories. To keep the generated diagrams simple, understandable, and free of visual clutter we visually encode the generated dataset into the cells of a matrix. Apart from just incorporating one individual metric of the dataset into a matrix cell, we extend this standard visualization by a dimensional-stacking approach supporting the display of several of those metrics integrated into one matrix cell. To further improve the readability and pattern finding among those values, our approach supports a metric-based clustering and further interaction techniques to manipulate the data and to navigate in it. To illustrate the usefulness of the system, we applied it to an eye movement dataset about the reading behavior of metro maps. Finally, we discuss limitations and scalability issues of the approach.

Index Terms: H.5.2 [Information Interfaces and Presentation]: User Interfaces—Graphical user interfaces (GUI);

1 Introduction

Exploring and finding correlations among a group of data entities can become a challenging task, in particular, if the number of data entities exceeds a certain size in terms of number of metrics as derivable from eye movement data. This is typically becoming more serious, if we are interested in metric comparisons, not only individual ones but also sets of them, building a multivariate dataset for pairwise comparisons. Those data metrics can, for example, be the number of fixations, the average saccade length, the average fixation duration, or the average saccade orientations to mention a few [5, 8]. Comparing those metrics between pairs of eye tracking study participants can give additional insights into their common and different strategies, but also becomes a tedious task if the dataset grows large and unstructured having many dimensions.

To support the exploration of such a dataset scenario we designed a matrix-based visualization with which we are able to see all correlations between pairs of eye tracked people. Moreover, a matrix visualization is free of visual clutter [13] and additionally allows us to show several of the data features in each individual cell. This cell-stacking technique is useful, but it has drawbacks for comparison tasks if the data remains unstructured.

To solve this issue to some extent we implemented a metric-based clustering technique that works algorithmically fast and hence, focuses on efficient interactivity of the system. With our approach, we are consequently able to directly explore the correlation patterns of eye tracking study participants based on a list of user-defined data features.

For illustrative purposes, we applied our visualization technique to an eye movement dataset formerly recorded [11]. The original data consists of the recorded eye tracking data of 40 participants who were solving a path-finding task in 48 metro maps. The recorded data were first preprocessed into a high-dimensional dataset. From the visual and analytical concepts, we are able to extract visual patterns that can further be remapped to the data in order to derive knowledge from the eye movement data. Finally, we describe limitations of our approach and discuss scalability issues that are worth discussing for a future extension of this work.

2 Related Work

Analyzing eye movement data is difficult due to its spatio-temporal nature and the fact that a certain number of eye tracking study participants brings another data dimension into play, perhaps becoming big data at one point [2]. Visualization can be a helpful tool to explore such vast amounts of data [3], in particular, when we are interested in pairwise comparisons of eye movement trajectory data [1].

Matrix visualizations serve as a good candidate for supporting an analyst, since they scale to very large datasets using a pixel-based

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representation [14] and they do not suffer from visual clutter [13]. An issue of matrices is the ordering of both axes, i.e., vertically as well as horizontally, in particular when several data features have to be displayed in a matrix cell. Multivariate data generated for each of the pairwise comparisons generates relationships among individual multi-dimensional data entities worth exploring, but perceptually difficult to understand. Consequently, we have to enhance our matrix-based visualization by a metric-based clustering technique [6, 10] that builds some kind of grouping and hence, a structure among the pairwise data comparisons.

In particular for eye tracking data, there are several visualization techniques that explicitly focus on comparing individual eye movement trajectories (scanpaths). For example, the parallel scan paths [12] make use of an axis and show how the fixation sequences are changing over time, to better compare them to each other. Although comparison tasks are supported, such diagrams are not visually scalable to long sequences, many participants, and a certain number of generated eye movement data metrics.

3 Data Model

From the original dataset [11], we used only the data of 20 participants $\hat{P}_i$ who were looking at 24 stimuli s. A participant looking at a specific stimulus is then referenced as $\ddot{P}_{i,s}$.

In the following, we describe the used metrics and similarity calculation in more detail.

3.1 Eye Movement Metrics

For demonstration purposes, we have decided to use three common metrics in eye tracking: average fixation duration (M_2), average saccade length (M_3), and average task completion time (M_4).

Additionally, we used the similarity of transition matrices (M_1) as a metric [11]. A 3D transition matrix is computed based on all sub-scanpaths with three subsequent fixations. More precisely, the fixation labels were used to generate a 3D transition matrix by counting how often a particular label sequence occurred. Thereby, a 3D transition matrix was created for each scanpath, which was interpreted as a 1D vector. The similarity calculation is now reduced to calculating the Euclidean distance of two vectors.

For each metric, we calculate similarity values sv_{M_i} for each pair of participants $\widetilde{P}_{l,m}$ (for a given stimuli s). We denote the similarity values as sv_{l,m,M_1}, sv_{l,m,M_2}, sv_{l,m,M_3}, and sv_{l,m,M_4}.

In total, for 20 participants, we will have 80 different values for one participant in the form of $\bar{P}_l sv_{M_i}$, where $1 \leq l \leq 20$ and $1 \leq i \leq 4$.

3.2 Data Transformation

We calculate similarity values sv_{l,m,M_i} between two participants $\hat{P}_l$ and $\hat{P}_m$ based on metric M_i using the Euclidean distance (Equation 1) to find similarities between the reading behavior of participants based on their eye movement data.

$$sv_{l,m,M_i} = d(P_{l,M_i}, P_{m,M_i}) \;\; = \;\; || \;\; P_{l,M_i} - P_{m,M_i} \;\; ||_2 \qquad (1)$$

P_{l,M_i} is a scalar value in case of M_2, M_3 and M_4 whereas vector in case of M_1. In our example, this resulted in four similarity matrices of size 20×20. We combined them in one matrix of the same size, but with four similarity values in one matrix cell.

4 Visualization Technique

Our visualization technique uses dimensional-stacked rectangular sub-grids, where we added a sub-grid in each matrix cell. The sub-grid contains the calculated similarity values sv_{l,m,M_i}. They are stored in clock-wise direction. This is illustrated in Figure 2. We use Color Brewer palettes [7] to encode data into color for an improved visualization.

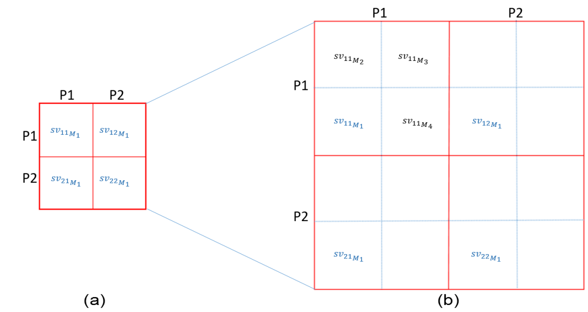


Figure 2: Stacking of dimensions.

4.1 Matrix Representation

There are many visualization techniques that can be used to show multi-dimensional data. In general, it is very easy to use a matrix-based visualization scheme for visual exploration as shown in Figure 1, but it becomes more challenging with an increasing number of attributes. This is in particular the case, if a larger number of matrices is involved, where each encodes the information of one metric.

To overcome the problem of comparing several matrices, we introduced a matrix-based visualization that we used to explore the features extracted from eye movement data. A matrix cell is used to encode multiple similarity values computed with Equation 1, following the concept of dimensional stacking: embedding dimensions within other dimensions [9].

4.2 Metric-Based Clustering

We have used agglomerative hierarchical clustering of the participants $\hat{P}_l$ for each chosen metric for the visual exploration. Hierarchical clustering is one of the mainstream clustering methods that is generally applicable to most types of data with a complexity of $O(N^2 \log N)$. It does not require any predefined parameter and, hence, is suitable for handling real-world data where finding a suitable set of parameters can be tricky [4]. A dendrogram is then generated for all the clustered results for exploring the similarity among participants for all the four metrics, shown in Figure 3.

5 Case Study

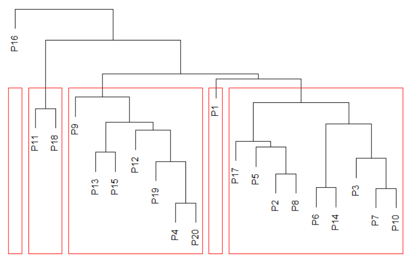
We used eye movement data from a previously conducted experiment about the reading behavior of metro maps [11] to demonstrate the effectiveness of our visualization. The stimulus chosen for this case study is the colored version of the metro map of Düsseldorf. The eye movement data were recorded by a Tobii T60XL eye-tracking system with a sampling rate of 60 Hz. We used the recorded data of 20 participants.

We compared the Euclidean distance for each metric during the hierarchical clustering to quantify similarities between groups of participants. The results of the clustering are depicted in Figure 3.

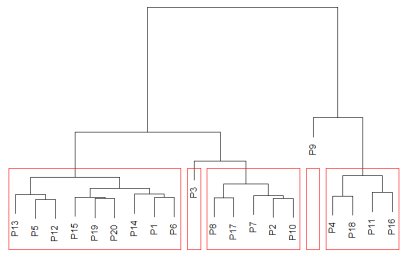
As stated in the original work [11], each stimulus was assigned to one of four groups depending on the average solution time of the stimulus over all participants.

Clustering was performed for each of the groups, resulting in three clusters per group. The clustering was performed based on the 3D transition matrix of each scanpath. One matrix had a size of 12^3 (12 labels per dimension) and corresponds to M_1. The authors of the original paper [11] did not comment on the groups of participants in particular, which we are able to do with our method.

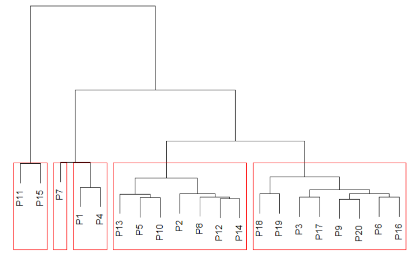
In principle, we expect the same behavioral pattern in the case of our approach, where we applied agglomerative hierarchical clustering on the distance matrix calculated from the same high-dimensional feature vector. In Figure 3(a), we can see that we also



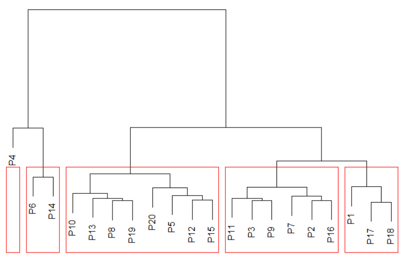
(a) M_1



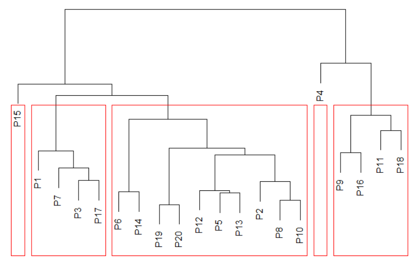
(b) M_2



(c) M_3



(d) M_4



(e) Weighted average of all metrics

Figure 3: Hierarchical clustering dendrogram of four metrics: M_1 (path transition), M_2 (fixation duration), M_3 (saccade length), M_4 (completion time), and weighted average of all metrics.

get three clusters, if we exclude clusters of size one.

This motivated us to find the groups of participants on the basis of other metrics of eye movement data. By applying a clustering on the similarity matrix of feature M_2, we got a similar structure with three strongly connected groups, but with a different grouping of participants as shown in Figure 3(b), and Figure 1(b) with three separated rectangular blobs, where P_3 and P_9 add to the exception list.

Similar observations were made elsewhere. In case of metrics M_3 and M_4, we could see different patterns in Figure 3(c) and Figure 3(d) respectively, where two groups of participants are strongly connected while one or two groups could be formed from the rest of the participants, resulting into more than three groups with strong proximity. This is also evident in Figure 1(c) and 1(d) respectively, where we can find more than three rectangular blobs.

However, comparing all four metrics at the same time is challenging, while using multiple images. That led us to the generation of a dimensional-stacked matrix with four sub-cells within one matrix cell. We generated a dimensional-stacked matrix as shown in Figure 4(a), without any clustering and simply filled the sub-cells with distance values of all the participants for all the four metrics in clockwise direction, which follows the order shown in Figure 2. We could find the outlier behavior of P_4 for metric M_1 individually, but we are not in the position to say anything concrete as a whole, which is our main goal. In order to generate visible patterns, we adapted the order of the participants on the x- and y-axis according to the clusters produced by the hierarchical clustering using M_2. The result is shown in Figure 4(b). Here, the patterns are getting more distinct.

We tried to fill the dimensional-stacked matrix in the order of the clustered pattern of feature M_2. With the grouping of the participants according to M_2, we could see the overall divisions of groups motivated by the feature value M_2.

In this case, the result is changed to only one metric, but it would be better to find an ordering that includes all metrics. Therefore, we created a numeric value based on the weighted sum of all available metrics. For simplicity, we have chosen a weight of 0.25 for all metrics. This led to a different order of participants and to a visualization with even more visible patterns (see Figure 4(c)). The detailed visually inspected annotation of Figure 4(c) shows the four different groups of participants. We further classify these groups into sub-groups; for example, group C is further sub-divided into C_1, C_2, and C_3. On the basis of the visual inspection method, we see that a part of group B (i.e., A_2 and A_3) belongs to group A, which shows that the participants are still not grouped properly. This indicates that the order of the participants can be further improved to achieve a better separation of different classes.

6 Limitations and Scalability

Although our visualization technique is useful for visually exploring eye movement metrics, there are several limitations, in particular, if the eye movement trajectories become long and if many of those exist like in experiments involving many study participants [2].

- **Algorithmic issues:** The applied clustering algorithm has to work rather fast to achieve an interactively responding visualization system. Since the clustering algorithm depends on the number of eye movement trajectories, the number of study participants plays a crucial role in this respect. The lengths of the trajectories are also important, not for the clustering, but for the data preprocessing into eye movement data features.

- **Visual scalability:** Due to display limitations, only a small number of metrics comparisons can be displayed in a single static diagram. If the matrix cells are split due to an increasing number of metrics, the display regions for each individual comparison become rather small, leading to problems while visually comparing the displayed data.

- **Perceptual challenges:** Since color is used as a visual variable to represent the set of pair-wise compared metrics, color perception issues play an important role when interpreting the visualization. To mitigate this problem, we allow the user to interactively select a color palette from a given repertoire.

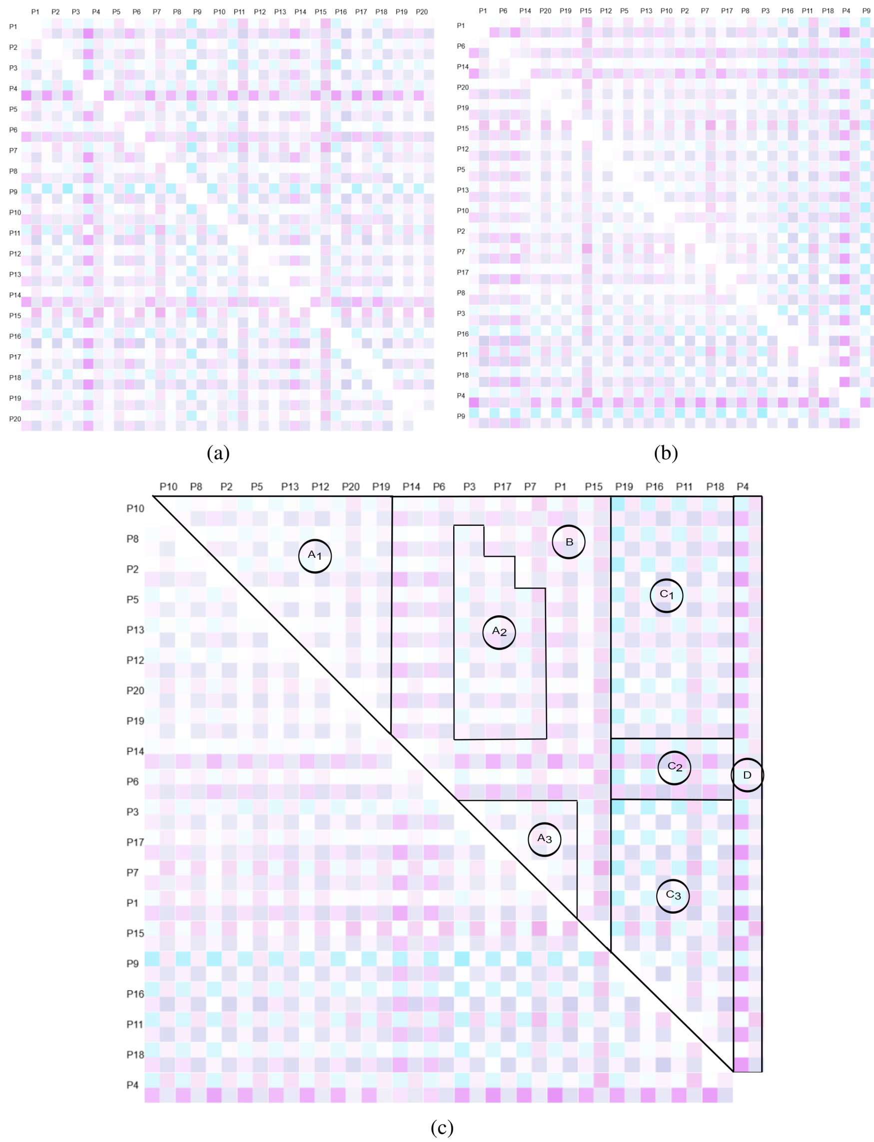


Figure 4: Dimensional-stacked matrix visualization with different ordering along the axes: (a) ordering according to participant ID, (b) ordering based on clustering according to metric M_2, (c) ordering based on clustering according to the weighted average of all metrics. A, B, C, and D are areas that exhibit similar visual properties and represent the four overarching classes. A and C are further sub-divided into sub-classes.

7 Conclusion and Future Work

We have presented a visualization to find patterns within data based on multiple metrics utilizing a similarity matrix. In order to use a single matrix for each metric, we applied the concept of dimensional stacking. The effectiveness of this method is demonstrated on eye tracking data. Furthermore, we show that the order of elements of the x- and y-axis highly influences the visible patterns of our approach that is mainly driven by the ordering of the participants in a group. Therefore, we discuss possible ways to improve the order. Still, the order of the elements is an issue and we have to work in the future on the optimization of the order. We currently do not have much interactive filtering and ordering techniques, which we will be addressing in the future, to enable a desired order of the participants with different combinations of weighted metric values. We also want to change the representation of the metrics from small rectangles to a possible radial design in order to address the issue of non-squared numbers of metrics.

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