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Identifying Similar Eye Movement Patterns with t-SNE

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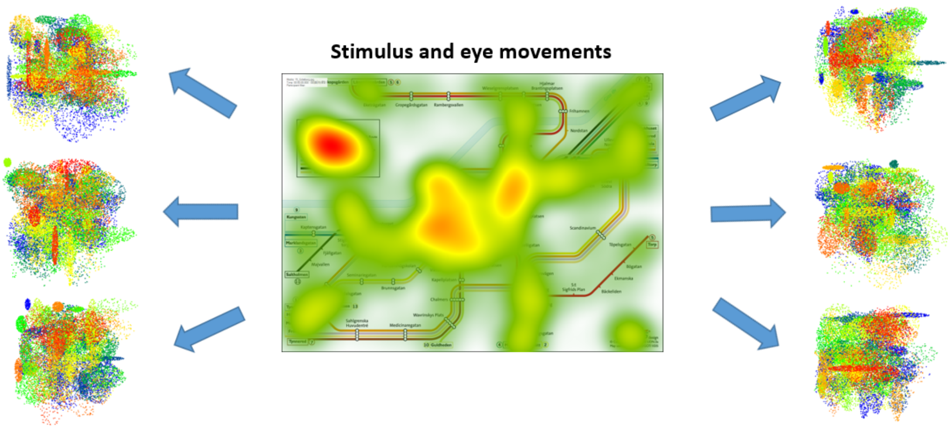

Figure 1: *Center view: A metro map stimulus from an eye tracking study overplotted with a visual attention map. Surrounding views: Scatterplots depicting visual scanning behaviors, projected to two dimensions, can be derived from the eye movement data. The visual outputs are depending on the metro map stimuli to be analyzed and the parameters given in t-SNE.*

Abstract

In this paper we describe an approach based on the t-distributed stochastic neighbor embedding (t-SNE) focusing on projecting high-dimensional eye movement data to two dimensions. The lower-dimensional data is then represented as scatterplots reflecting the local structure of the high-dimensional eye movement data and hence, providing a strategy to identify similar eye movement patterns. The scatterplots can be used as means to interact with and to further annotate and analyze the data for additional properties focusing on space, time, or participants. Since t-SNE oftentimes produces groups of data points mapped to and overplotted in small scatterplot regions, we additionally support the modification of data point groups by a force-directed placement as a post processing in addition to t-SNE that can be run after the initial t-SNE algorithm is stopped. This spatial modification can be applied to each identified data point group independently which is difficult to integrate into a standard t-SNE approach. We illustrate the usefulness of our technique by applying it to formerly conducted eye tracking studies investigating the readability of public transport maps and map annotations.

CCS Concepts

• ***Human-centered computing*** $\rightarrow$ ***Visualization techniques;***

1. Introduction

Eye movement data contains information about the who, when, and where, i.e., it consists of spatio-temporal visual attention aspects differing between eye tracking study participants, but also over space and time. Moreover, several metrics can be derived from the data like fixation durations, saccade lengths, or saccade orientations and the like. Additional physiological data like pupil dilations, blood pressure, or galvanic skin response might be used to augment the pure eye tracking data [BBRW15] while also verbal feedback might have been recorded. Bringing it to one point, eye tracking data can become rather complex having a high-dimensional nature and hence, making it hard to analyze and to visualize with the standard methods [BKR*17].

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In particular, identifying similarities among the visual scanning strategies is challenging since the eye movements are difficult to be aligned to see those commonalities in the visual scanning behavior. This even worsens if more metrics [HNA*11, Duc03] and data properties are taken into account in the similarity detection process. For example, it might be of special interest if a group of people followed a similar path or attended a set of areas of interest (AOIs) in a certain order [AABW12]. Positively, these data aspects might be used to find insights in the scanpath data, in the form of similar scanning behavior over participants, space, and time, probably reflecting problems or design flaws in the corresponding stimulus.

In this paper we describe an approach based on the t-distributed stochastic neighbor embedding (t-SNE) [vdMH08, vdM14] that is useful for reducing high-dimensional data into a lower dimension, in particular if we are interested in keeping low-dimensional data points of similar high-dimensional points close together. For eye movement data in which the saccade sequences model the high-dimensional data points, low-dimensional non-linear manifolds like saccadic eye movement patterns can be inherent in the high-dimensional data. Consequently, t-SNE as a non-linear dimensionality reduction technique can be useful to group those similar high-dimensional data points in the lower-dimensional space and hence, to identify similar eye movement patterns. The resulting two-dimensional eye movement data can be visually represented by interactive scatterplots (see Figure 1) serving as an overview for the similarities among the eye movements over space, time, and participants.

To reach this goal, we first split the eye movements into subsequences (connected parts of scanpaths) and assign each subsequence a feature vector of quantities modeling certain user-selected properties of the eye movement data. These vectors are then used as inputs for t-SNE while the output in form of an interactive 2D scatterplot is useful to select a certain number of scanpaths that share similar properties. Those are reflected by their spatial neighborhood in the scatterplot, i.e., groups of data points modeling the high-dimensional eye movements. To further strengthen the sometimes merged or wide-spread point groups we add another force-directed placement [FR91, KK89] process applied to the output of t-SNE that is able to modify each point group separately. By this interactive placement modification strategy we are able to identify similar scanning behavior over space, time, and participant groups.

We illustrate the usefulness of our approach by applying it to eye movement data from two formerly conducted eye tracking studies investigating typical tasks in metro map design [BKW14, NOK*17] and map annotation [NHB*17].

2. Related Work

If the task is to identify similar visual scanning strategies [AABW12], not globally but also locally, among eye tracking study participants, in the stimulus space, and over time [KFBW16, KBB*17], this can become a challenging problem for both, data analysis and visualization. For example, for analyzing local features in scanpaths [DDJ*10], those have to be separated first into several subsequences which soon produces thousands of trajectories attached with additional data properties or derived metrics [HNA*11, Duc03].

Algorithmically analyzing them typically has a high runtime complexity but even then the output of these algorithms [KRS*17] can be immense and is composed of texts and quantities that can hardly be explored for similarities, differences, or insights in general. Using only visualization instead [BKR*17], like gazeplots [SPK86], scanpath visualizations [RHB*14], or visual attention maps [SM07, Bur16] soon lead to degradations of performance at some task caused by visual clutter [RLMJ05] or aggregation over space, time, and participants.

More sophisticated visual analytics techniques that combine automatic analysis and interactive visualizations [BJK*16] also have problems with the vast amount of spatio-temporal data and can seldom output similar scanning behavior on different temporal granularities, stimulus regions, or groups of participants. They typically take the entire scanpath for each participant as input and output a measure expressing the degree of similarity. In most cases such a measure is then taken for clustering the set of scanpaths and only represent the clustered output visually without showing a scalable overview about similar eye movements as a starting point for further data explorations. For example, gaze stripes by Kurzhals et al. [KHH*16] make use of image thumbnails representing the scanpaths while the image features might be used to guide a hierarchical clustering algorithm. Although this strategy might be applicable to thousands of scanpaths, the output in form of horizontal stripes is not visually scalable for such an approach nor does it easily depict the local and global structure of the data. Generally, Pezzotti et al. [PLvdM*17] investigated the use of t-SNE for progressive visual analytics focusing on improving the interactivity of analytics techniques. Jianu et al [JDL09] argue that a combination of original visualizations like 3D models with lower-dimensional representations, typically generated by a force-directed-based 2D embedding, can lead to easier navigations and improved data explorations. Chen et al. [CDZ*09] also rely on this combination of high- and low-dimensional representations and provide an interactive technique for the exploration of DTI fibers while the reduction is based on MDS. Rössl and Theisel [RT12] introduce a concept for embedding streamlines in 3D vector fields by preserving the Hausdorff metric in the streamline space.

Although the aforementioned ideas show some benefits, they are not easily adaptable to eye movement data. In our work we transform scanpaths to high-dimensional data points by letting the data analyst first cut each scanpath into subsequences of a certain length and then map a feature vector to each of the subscanpaths. Those vectors are built by a set of eye movement data-characteristic quantities that model high-dimensional data. This dataset might be visually represented by standard techniques like parallel coordinates [ID90, HW15], scatter plot matrices [EGSC13], or glyph-based techniques like star plots [Fri91] or Chernoff faces [Che73]. But as a negative consequence, the thousands of scanpaths consisting of many dimensions each (given by the feature vector) make traditional visualization techniques non-scalable, i.e., they are rather cluttered (parallel coordinates) or do not fit on the screen (scatterplot matrices or glyph-based diagrams). Moreover, it is not possible to explore the high-dimensional data for local and global structure, i.e., scanpath similarities or dissimilarities. Consequently, for getting an overview and to identify the scanpath similarities, we need a more advanced and scalable approach that first reduces the high-dimensional data into a low-dimensional representation in which the data can be visually projected by preserving the similarities as well as possible, while preserving as much of the significant high-dimensional structure of the data as possible in the lower dimension.

We got inspired by t-SNE [vdMH08, vdM14] as a non-linear dimensionality reduction technique since the technique is able to preserve the local as well as the global structure of the data. It also focuses on grouping data points in 2D that lie on a low-dimensional non-linear manifold in the high-dimensional data which is problematic for linear techniques like PCA [Hot33] or MDS [Tor52]. Moreover, it promises to find a better solution to the crowding problem that is typical for many other techniques like SNE [HR02] while existing techniques [LV07] typically have problems when it comes to retaining the local as well as the global structure of the data. Since we still found the crowding problem and the user-defined number of iterations problematic for our datasets [WVJ16], even after checking several runs of t-SNE, we further extend t-SNE by another step applying a force-directed [FR91, KK89] kind of data point replacement in the 2D scatterplots. This post processing replacement strategy can be applied on each of the identified data point groups separately with the goal to better visually reflect the data point groups and hence, to accelerate the visual similarity identification process.

3. Data Model and Transformations

Eye movement data typically consists of several data dimensions [BBRW15] and can be complemented by additional properties and derived metrics [HNA*11]. Moreover, additional physiological data or measurements can augment the traditional eye movement data that comes in the form of spatio-temporal scanpaths. In this section we illustrate how the eye movement data is transformed to make it applicable to t-SNE and how the final results of the embedding and additional force-directed placement algorithm are generated and look like. Figure 2 illustrates this process starting with scanpaths depicted in a 2D stimulus, generating feature vectors modeling high-dimensional data, and applying t-SNE for dimensionality reduction.

3.1. Eye Movement Data

We model eye movement data as scanpaths recorded during eye tracking experiments in which participants are shown a stimulus and they are given a task to be solved. The visual scanning strategies might be explored to identify design flaws or problematic issues in the stimulus in order to improve it or to exchange it by another (possibly better) one.

We mathematically model a scanpath of an individual participant $i \in \mathbb{N}$ by

$$S_i := \left(p_{i,1}, \ldots, p_{i,n_i}\right)$$

where $p_{i,j} \in \mathbb{N} \times \mathbb{N}$ models the fixation points in a two-dimensional stimulus. It may be noted that each scanpath S_i may have a different length since study participants typically answer the tasks differently.

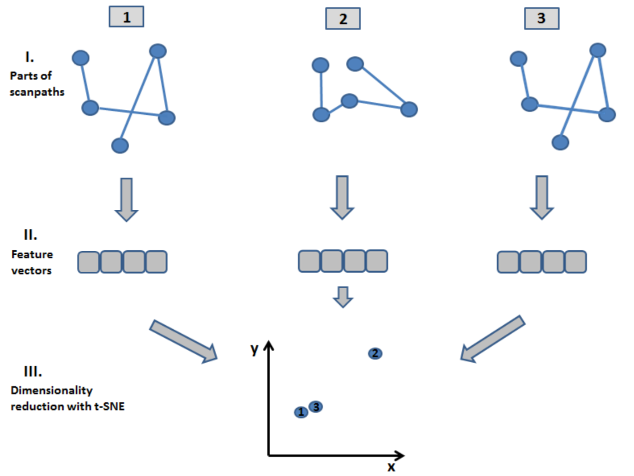

Figure 2: *An illustration of the dimensionality reduction applied to several scanpaths. Feature vectors are computed first that serve as input for t-SNE. The output in form of a 2D scatterplot is color coded based on a user-defined criterion like space, time, or participants. The point groups based on such a criterion are further transformed by a force-directed placement strategy that works on each group independently. Interactions with the 2D scatterplot are useful to link the grouped data to the original stimulus and the original scanpaths.*

3.2. Metrics and Feature Vectors

There are several metrics derivable from eye movement data. All of them might be used for a dimensionality reduction with t-SNE, as far as they have a quantitative nature, i.e., they are real-valued numbers. For example, fixation durations, fixation locations in AOIs, saccade lengths, saccade orientations, and the like all build metrics that produce values worth investigating.

If scanpaths are under exploration, those metrics can be applied to each fixation or saccade resulting in a list of metric values for each scanpath. The number of values under observation can be selected by the data analyst, but it may be noted, that the more metrics are taken into account, the smaller the probability typically becomes that two scanpaths are similar. The mapping of such high-dimensional data to a lower (typical 2D) dimension gets more difficult and hence, the more metric values are contained the more difficult and the more time-consuming the dimensionality reduction process will be. Moreover, individual scanpaths of a certain length can be split into a list of subscanpaths of a smaller length. This process supports the detection of local, in-between, scanning strategies, either for one participant or several of those.

An example would be a set of n scanpaths (maybe from n eye tracking study participants) while each scanpath is split into equally long shorter scanpaths of length m (number of fixations is m). By doing this we get another set of typically many more than n scanpaths while each of those consists of m fixations and $m-1$ saccades. Now, a data analyst might be interested in feature vectors that describe the sequence of fixation durations in each of these smaller scanpaths. By doing this, we obtain a set of m-dimensional vectors that may contain some patterns based on the fixation duration sequences.

For instance, there might be groups of vectors that are similar while others are dissimilar. A similarity among such vectors reflects that there is a similar visual scanning strategy that can be further linked to time, space, or participant information. To algorithmically detect those similarity patterns we need dimensionality reduction techniques that are able to find a good mapping between the high-dimensional data to a lower dimension, for example, in 2D in order to project the dimensionally-reduced data to a 2D scatterplot. This simple and intuitive visualization can then be used to interactively find patterns in form of point groups sharing a similar property while they can be linked to the original eye movement data.

3.3. Dimensionality Reduction with t-SNE

The goal of the dimensionality reduction using t-SNE is the projection of high-dimensional eye movement data to a low-dimensional space. This could be done in many ways but the challenge is to keep similar points in the high dimension also similar in the low dimension and also dissimilar points in the higher dimension dissimilar in the low dimension while also preserving the structure of non-linear low-dimensional manifolds. If the projection is done in a wrong way, some kind of lie factor in the visualization is generated which would possibly lead to misinterpretations for the visual observer.

Traditional dimensionality reduction techniques like PCS or MDS are linear techniques that do not support the detection of non-linear low-dimensional manifolds. Moreover, non-linear techniques like CCA, SNE, Sammon mapping, Isomap, MVU, LLE, or Laplacian Eigenmaps have been used as alternative approaches, but those are not able to preserve the local and global structure [vdMH08]. Hence, we base our concept on the non-linear t-SNE approach. In particular, t-SNE is useful for eye movement data in which the data can be located on lower-dimensional manifolds, like subsequences of scanpaths in which similar orientation sequences are contained while the rest is noise in the higher dimension, for example, generated by calibration errors or inaccuracies. Specific characteristics of eye movement data can be taken into account by the data analyst when experimenting with the transformation of the scanpaths into feature vectors based on typical metrics.

In the t-SNE [vdMH08] approach, this projection is achieved by modeling the similarities or dissimilarities of two high-dimensional points by conditional probability distributions. To compute the conditional probabilities we follow the same strategy as in [vdMH08] and use a t-student distribution with one degree of freedom for the high-dimensional as well as the low-dimensional data. Finally, those distributions are tried to match by applying the Kullback-Leibler divergence whereas the sum over all data and projection points is minimized following a gradient descent strategy. The original idea has been extended and improved a lot, for example, by accelerating it exploiting a tree-based algorithm [vdM14].

In this paper we follow this strategy described by van der Maaten and Hinton. The goal of our approach is to let the data analyst decide how to interactively build the feature vectors out of a set of user-defined splitting of scanpaths and then apply dimensionality reduction in form of t-SNE to reduce the complexity of the data and to identify similar eye movement patterns. On top of this, interaction techniques can be applied in order to annotate or filter the represented 2D scatterplot points by categorical information like space, time, or participants. These combinations of scanpath information reduced to lower dimensions and extra data annotations build a novel idea for the application of dimensionality reduction techniques, but also for eye movement data analyses.

The resulting 2D embedding (like in a scatter plot) can be further visually enhanced by adding color coding to the points. Those colors could indicate a category given by an extra feature of the data, for example, areas of interest, time periods, or participant groups.

3.4. Force-Directed Post Processing

We modified the projection result of t-SNE by adapting it for our purposes. This means it should be easier to separate the point groups in the 2D visual embedding if t-SNE is not able to really separate the point groups. To reach this goal, we further transform the output of t-SNE by attracting and repelling forces between the points in a certain user-defined category, for example, belonging to the same AOI, happening in the same time period, or done by the same individual or group of participants. This gives a clearer picture of the sometimes overlapping points. This feature can be used for example, to further spatially aggregate the points while still preserving their group structure and hence, providing a better view on the remaining point groups. The user can decide to apply this feature on demand. Integrating those group-based forces into t-SNE itself is challenging since t-SNE should be applied to the entire high-dimensional dataset first to depict inherent data structures or manifolds and then this additional force-directed placement (t-SNE itself is already force-directed) should be done as a post process.

Those point attractions can be done by a user-defined parameter deciding about the attraction strength and the attraction direction, i.e., how close the points are moved together, which is similar to force-directed placement in graph drawing. To better allow the building of specific characteristic shapes of the point clouds we let the user decide about those directions, i.e., the points are either grouped to circular or elliptical shapes. The benefits of such point position modifications occur if t-SNE itself is not able to produce uncluttered 2D representations like in the crowding problem when placing too many points of different categories in the same display region. However, if the resulting 2D diagram is already useful, the post processing in form of this force-directed placement should not be applied.

Moreover, to support several groups of points belonging to the same category to be separable and not merged together, we follow a certain layout strategy. This algorithm first computes the average distance of all pairwise distances of all points in a certain group. Then, as a next step, all point pairs whose distances are lying below the average distance are forced to attract each other while those points whose distances are bigger than the average distance are forced to repel. It may be noted that the attraction should not be too large, i.e., not that many iterations should be applied in order to not merge all of the points into a group of nearby points. This would destroy the global placement of points that was generated by t-SNE from the previous step. The force-directed placement process is just an additional add-on feature to further support the group identification. The user can decide how strong the effect should be applied to the original 2D projection of the data.

4. Visualization of t-SNE Results

The visual encoding of the projected data is important in order to rapidly identify groups of points that indicate a certain similarity property. This property depends on the user-defined feature vectors and the splitting of the scanpaths into shorter subsequences. Moreover, the observer can interact with the 2D scatterplots in order to get more insights out of it. For example, an additional color coding depending on categorical data can show point distributions for certain aspects while the groups can be selected in order to filter the eye movement data for a certain characteristic feature, like all scanpaths following a certain spatial pattern. Moreover, the original point group shapes computed by t-SNE are interactively modifiable by a post processing in form of a user-defined force-directed placement.

4.1. 2D Scatterplots

We have chosen a simple visualization technique for the 2D projection of the high-dimensional data which is a typical diagram type for dimensionality reduction techniques. Each feature vector becomes a point in the 2D plane while the axes of the 2D plane are just used for the embedding or projection of the data following the similarity and dissimilarity properties. The x- and y-values at the axes do not explain anything about the strengths of the corresponding 2D points like in traditional scatterplots. In our case they just model the property of the neighborhood of data points. Even the global distance between point groups is no argument for the strength or weakness of their similarities.

t-SNE is responsible for generating the mapping of the points, i.e., each run of the t-SNE algorithm typically causes a different setting of the scatterplot, i.e., the location of the points might be a totally different one, but the grouping structure remains similar. This aspect is not a big problem for our approach since we are mostly interested in the grouping behavior that can be used to identify common scanpath patterns in the spatio-temporal eye movement data. Hence, the t-SNE algorithm can be run several times until the data analyst is confident with the outcome and if the crowding issue of data points is still problematic the additional force-directed placement strategy might be helpful.

Additional visual encodings can be added to the standard scatterplot like point thicknesses, point shapes, or point colors with the goal to reflect more than one category at once. If more than one visual variable is used for each point it may be noted that the visual observer may then be confronted by a conjunction search, i.e., there is no pop-out effect any more as in pre-attentive processing. Hence, identifying patterns might be challenging. It may also be noted that more complex features might be added like the scanpath's trajectory or stimulus image thumbnail as a miniature representation, although this will produce vast amounts of overdraw, occlusion, and visual clutter. Eye movement data has the great benefit that it can be observed from different perspectives and hence, experimenting with additional visual variables might be a good strategy to explore this high-dimensional data.

4.2. Interaction Techniques

Apart from inspecting the static scatterplot with the embedding of the high-dimensional feature vectors, the data analyst is able to apply a certain number of interaction techniques. In general, an overview is first provided that depicts all data points in 2D serving as a starting point for further explorations. The goal of those interactions is to reduce the amount of displayed data or to inspect it from different perspectives. Finally, a linking to the original stimulus can support setting the found insights into context to the real and original eye movement data.

- **Category indication:** After t-SNE generated a 2D embedding of the high-dimensional data, the user can apply an additional visual encoding of categorical information. This can be done by color coding, shapes, or point thicknesses. It may be noted that too many features can distract the diagram and may lead to problems when interpreting the data.
- **Category filter:** The embedded data can also be restricted or filtered to a certain kind of category. This reduces the visual clutter effect in the diagram and may lead to novel insights that might not have been found by the original unfiltered scatterplot.
- **Scanpath splitting:** Before applying t-SNE the user can decide to split the scanpaths into equally long subsequences. This parameter is deciding for the number of feature vectors to be taken into account as high-dimensional data to be embedded into the plane.
- **Feature vector assignment:** Eye tracking metrics as well as additional data can be used for describing a scanpath. It may be noted that the more features are given the more dimensions have to be taken into account possibly leading to many dissimilar points.
- **Force-directed placement:** The final step of our algorithm can be used to merge groups of points belonging to a similar category spatially closer together. In this step the user can adapt several parameters interactively like the number of iterations, the strengths of the attraction, or the directions of attraction.

It may be worth saying that there are many more interaction techniques, too many to describe all of them in this paper. Moreover, we plan to add some more in the future.

5. Application Example

We applied the extended t-SNE approach to eye movement data as described in the former sections. First we preprocessed the data from two formerly conducted eye tracking experiments investigating visual scanning strategies in metro map designs [BKW14, NOK*17] and map annotations [NHB*17].

The feature vectors could be modeled by various alternatives. For illustrative purposes we look at the saccade sequences of subscanpaths and try to figure out if the saccade orientations can give

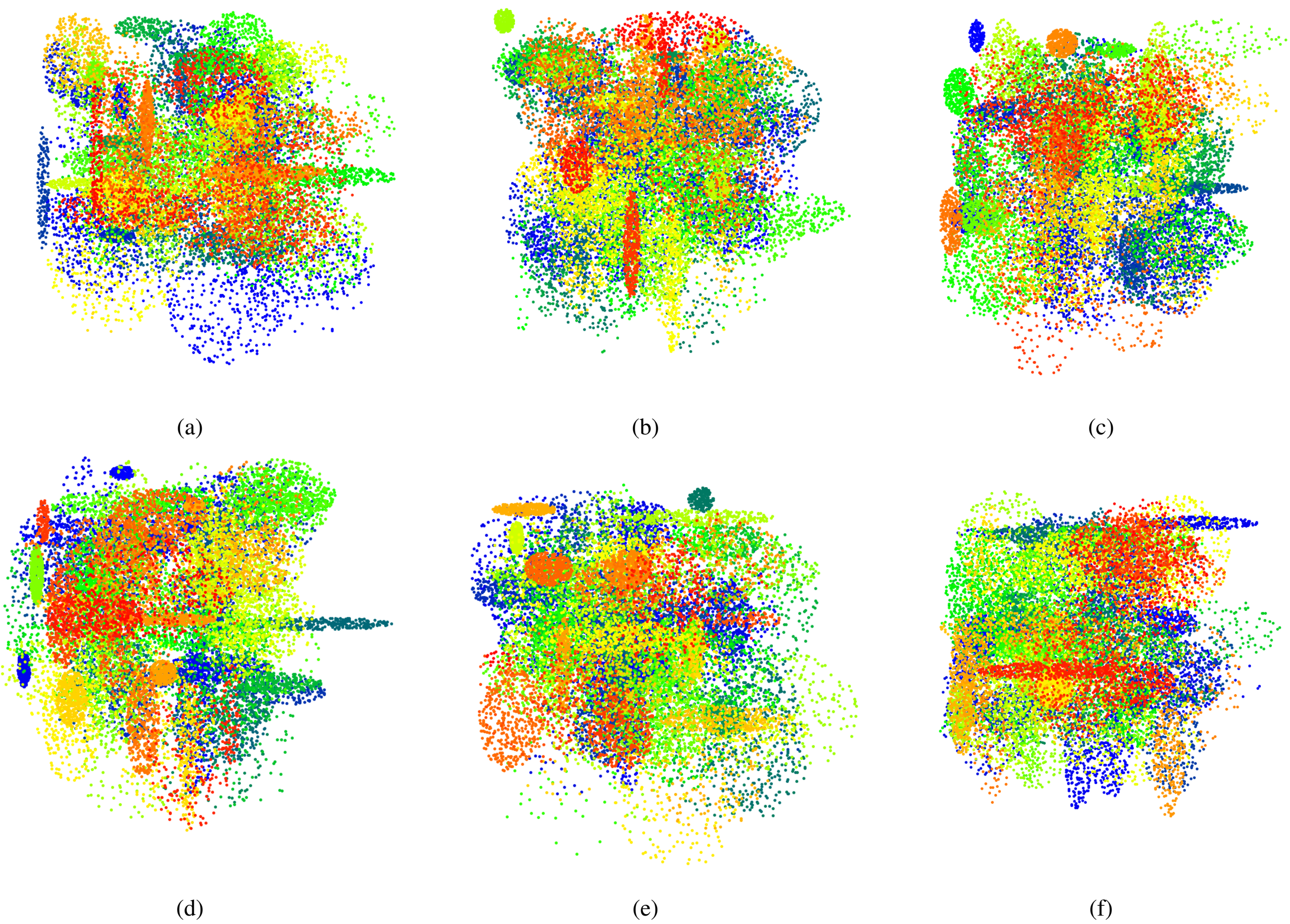

Figure 3: *Scatter plots showing the similarities of subscanpaths of lengths 7 while taking into account the 6 saccade directions: number of iterations 500, perplexity 50. The color coding shows a space subdivision into AOIs. Route finding tasks in metro maps are asked: (a) Berlin. (b) Antwerp. (c) New York. (d) Hamburg. (e) Frankfurt. (f) Venice.*

insights about similar visual scanning strategies. To reach this goal, each scanpath is first transformed into angle sequences expressed by value pairs using Euler's formula. We experimented with several subscanpath lengths while lengths 7 and 10 were used as example applications. It may be noted that longer scanpaths lead to larger feature vectors and hence, to more dissimilar points. If the length is too small, then the scanpaths would show too many similarities and shorter subsequences are not that significant for the visual analysis. In the following subsections we demonstrate insights from concrete eye movement data examples and how particular configurations and parameters can be applied to manipulate the visual output and perspectives on the data.

5.1. Metro Maps

One of our eye tracking studies investigates the readability of different metro maps. A typical route finding task is asked while 40 participants took part in the study. All the maps were designed by the same characteristic style to achieve similar preconditions for the eye tracking study.

For illustrative purposes we split the scanpaths of the study participants for the same stimulus into sequences of length 7, i.e., the scanpaths are composed of 6 saccades. It may be noted that any other splitting number could be applied, we just take 7 to show the usefulness of our approach while we also experimented with other parameters. Generally, if the length of the sequences is too high, there will not be many similarities, on the other hand, if it is too low, there will be too many. This challenge of finding a good length value can be solved interactively.

After having done the split operation, we obtain a set of scanpaths consisting of 2,500 to 3,500 scanpaths. The feature vectors are again given by the saccade orientations given as angular value pairs. In this exploration setting we do not apply a time-based categorization, but we apply an area of interest-based one. This should show us, which similar scanpath patterns occur in which AOIs. For

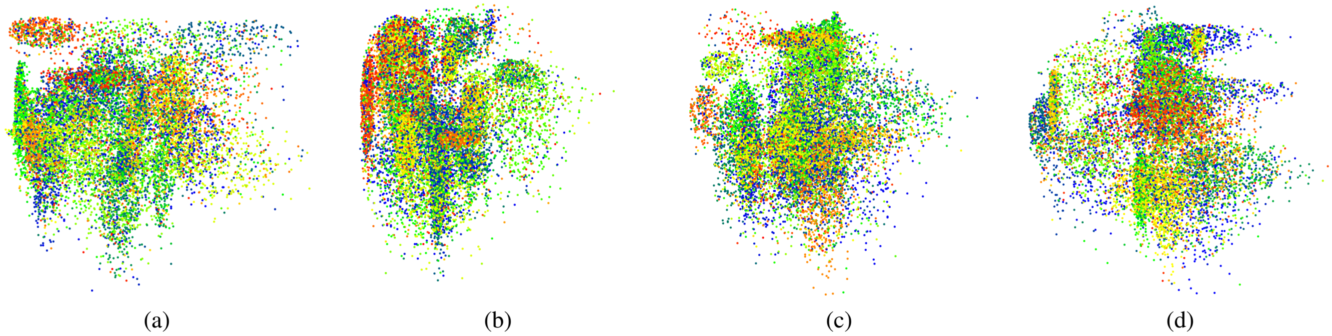

Figure 4: *Similarities of subscanpaths of lengths 10 while taking into account the 9 saccade directions: number of iterations 500, perplexity 50. The color coding shows a space subdivision into participants: (a) Free search. (b) Atlas search. (c) Grid-based search. (d) Partial links.*

the AOI subdivision we chose a grid-based splitting into 10 times 10 grid cells. The granularity can be adapted on users' demand.

Figure 3 shows that there is some kind of clear structure for the AOI subdivision that holds in nearly any metro map shown in the figure. We further enhanced the cluster structure by applying a force-directed placement with 40 iterations. Each color indicates an AOI and it is clearly visible that the AOIs contain similar scanning strategies. This phenomenon can be explained by the route finding task which has to be done in a structured way by following metro lines and changing trains at interchange points.

This is an example where the color coding could be enhanced by an additional shape encoding for the time periods. Moreover, also the metro line color might be used for the point colors.

5.2. Map Annotations

Finding labels in geographic maps can become a tedious task if not supported by additional indicators. In an eye tracking study several map annotations were compared in terms of which scanning strategies were applied by the study participants. In this study 40 participants were confronted by artificially generated maps with randomly placed labels.

The goal was to find the given label in the map by using one of the three annotations. This search improvement effect was compared to a free search, i.e., the map was not annotated by any kind of additional symbol or feature.

Figure 4 shows four different scenarios for scanpaths of length 10 with 9 saccades. The feature vectors are computed by using the saccade orientations as angular value pairs. In this example we chose longer scanpaths since the participants had to follow longer steps and we hypothesize that different patterns occur than in the other two experiments in terms of the lengths of the saccades, i.e., the participants did longer jumps with their eyes. In this example, we encode the participants by color, i.e., each individual participant gets his own color.

In (a) we can see the free search scenario but even there a certain kind of similar scanpaths exists. It seems as if the participants applied a certain kind of search strategy to find the label. Although there are clusters, the individual cluster points have mostly different colors indicating that several participants did a similar search behavior.

In (b), (c), and (d) we can see a point group structure. From the results of the former study we know that people are able to apply the map annotations in a way that they can solve the task more rapidly than in the free search scenario. However, from the t-SNE examples and the scatterplots we cannot really see a difference between point group structures. In (d) the structure seems to be a bit stronger, and there seems to be a clearer color coding in terms of study participants. The partial link representation demands for following an invisible line given by the partial link, i.e., the label search task becomes a pointing task, meaning the participants mostly looked into a similar direction which may be the reason for the larger point groups in terms of number of elements in this example.

6. Conclusion and Future Work

In this paper we investigate t-SNE as a non-linear dimensionality reduction technique applied to eye movement data. We first split the scanpaths from several eye tracked people into subsequences of a certain user-defined length. Then feature vectors can be computed for each scanpath subsequence based on typical eye tracking metrics or additional data. Those feature vectors build a set of high-dimensional data consisting of several dimensions. Finding insights in those high-dimensional datasets is challenging and hence, dimensionality reduction comes into play projecting the high-dimensional vectors to a lower dimension like a 2D scatterplot. To mitigate the situation of the crowding problem we further apply a force-directed approach for each point group category separately to further emphasize the group structures. Interactions can be applied to filter the data based on the visual output which further supports the pattern and insight detection in the eye movement data. For future work we plan to add additional visual encodings for the lower-dimensional data while we will also experiment with other dimensionality reduction techniques in order to understand the differences of the algorithmic outputs. Those techniques might be linear ones like principal component analysis (PCA) or multidimensional scaling (MDS) as well as non-linear ones like isomap or locally linear embedding (LLE) and the like.

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