Eyetrace2014
Eyetracking Data Analysis Tool

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Abstract: Over the last years eye tracking became more and more popular. A variety of new eye-tracker models and algorithms for eye tracking data processing emerged. On the one hand this multitude of hard- and software brought many advantages, on the other hand the diversity of devices and measures impedes the comparability and repeatability of eye-tracking studies. While supply of eye tracking software is high, the functioning of the algorithms, e.g. how fixations are identified, is often intransparent and unflexible. The *Eyetrace* software bundle approaches these problems by providing a variety of different evaluation methods compatible with many eye-tracker models.

Eyetrace2014 combines state-of-the-art algorithms with established approaches and provides a continuous visualization of the analysis process. All calculations provide user adaptable parameters and are well documented and referenced in order to make the whole analysis transparent.

Our software is available free of charge well suited for exploratory data analysis and education (http://www.ti.uni-tuebingen.de/Eyetrace.1751.0.html).

1 INTRODUCTION

During the last decades, eye-tracking became resident in many fields of application. Besides its traditional use in psychology and market investigation, eye-tracking also found its way into medicine and natural sciences. Going hand in hand with the increase in the number of eye-tracking devices and vendors, the variety of software for the evaluation of the produced data increased steadily (SMI begaze, Tobii Analytics, D-Lab, NYAN, Eyeworks, ASL Results Plus, Gazepoint Analysis, ...). Major brands offer their individual analysis software with ready-to-run algorithms and preset parameters for their eye-tracker model and typical application. However, all of them share a common feature base (such as visualizing gaze traces, attention maps, gaze clusters and calculating area of interest statistics) and distinguish in minor features.

Besides the financial effort and licensing restrictions, these applications usually can not be extended by custom algorithms and specialized evaluation methods. Not few studies reach the point where the manufacturer software is insufficient or very expensive, extension of the software is not possible and all data has to be exported and loaded into other programs e.g. Matlab for further processing. Furthermore individual calculations are often non-opaque or not documented in all necessary detail in order to allow comparison to studies conducted with different eye-tracker models or even different recording software versions.

Eyetrace supports a range of common eye-trackers and offers a variety of state-of-the-art algorithms for eye-tracking data analysis. The aim is not only to provide a standardized work flow, but also to highlight the variability of different eye-tracker models as well as different algorithms (such as fixation identification filters). Our approach is driven by continuous data visualization so that the result of each analysis step can be visually inspected. Different visualization techniques are available and can be active at the same time, i.e. a scanpath can be drawn over an attention map with areas of interest highlighted. All visualizations are customizable in order to visualize grouping effects, being distinguishable on different backgrounds and for color-blind persons.

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We realized that no analysis software can provide all the tools required for every possible study. Therefore the software is on the one hand extensible and offers on the other hand the possibility for data export of all calculated values.

Eyetrace has its root in a collaboration between the department of art history (Brinkmann et al., 2014; Klein et al., 2014; Rosenberg, 2014) at the University of Vienna and the computer science department at the University of Tübingen, contributing new scanpath evaluation tools and algorithms. It consists of the core analysis component and a pre-processing step that is responsible for compatibility with many different eye-tracker models. The software bundle, including *Eyetrace2014* and *EyetraceButler* was written in C++, based on the experience of the previous version (EyeTrace 3.10.4, developed by M. Hirschbühl) as well as other eye-tracking analysis tools (Tafaj et al., 2011).

We are eager to implement state-of-the-art algorithms, such as fixation filters, clustering algorithms and data-driven area of interest annotation and we share the need to understand how these methods work. Therefore implemented methods as well as their parameters are transparent and documented in detail with original work referenced. We provide a standard set of parameters for the algorithms, but each of them can easily be changed from within the GUI.

Eyetrace is available free of charge for universities and educational institutions. It is on the one hand usable for complex scientific evaluations and on the other hand also a intuitive tool to get familiar with evaluation algorithms. Using *Eyetrace* for the practical part of an eye-tracking lecture it can help students to reach a deeper understanding of eye-tracking data analysis.

2 DATA PREPARATION

In order to make the use of different eye-tracker models convenient, recordings have to be preprocessed and converted to a common eye-tracker independent format. This step can also be used in order to splice a single recording into subsets (e.g. by task or stimulus) and for quality checking. This step is performed by *EyetraceButler*.

EyetraceButler provides a separate plug-in for all supported eye-trackers and converts the individual eye-tracking recordings into a format that holds information common to almost all eye-tracking formats: For both eyes it contains the x and y coordinate, the width and height of the pupil as well as a validity bit, together with a joint time stamp. For monocular eye-trackers or eye-trackers that do not include pupil data the corresponding values are set to zero. A quality report is produced that contains information about the overall tracking quality as well as individual tracking losses (Figure 1).

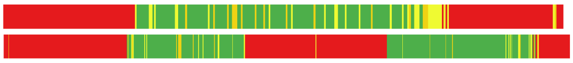


Figure 1: Quality analysis for two recordings with a binocular eye-tracker. The color codes measurement errors (red), successful tracking of both eyes (green) and of only one eye (yellow) over time. It is easy to visually assess the quality of a recording, even if the beginning and end of the measurement are of bad quality (top) or tracking is lost and regained during the experiment (bottom).

2.1 Supplementary Data

In addition to the eye-tracking data, arbitrary supplementary information about the subject or relevant experimental conditions can be added, e.g. gender, age, dominant eye, or patient status. This information is made available to *Eyetrace2014* along with information about the stimulus viewed. Using the provided information the program is able to sort and group all loaded examinations according to these values.

2.2 Supported Eye-trackers

The *EyetraceButler* utilizes slim plug-ins in order to implement new eye-tracker profiles. As of now plug-ins for five different eye-trackers are available, among them models of SMI, Ergoneers and *TheEyeTribe* as well as a calibration free tracker recently developed by the Fraunhofer Institute in Illmenau.

3 DATA ANALYSIS

3.1 Loading, Grouping and Filtering Data

Data files prepared by the Butler can be batch loaded into *Eyetrace* together with their accompanying information such as the stimulus image or subject information. Visualization and analysis techniques can handle subjects grouping by any of the arbitrary subject information fields. For example attention maps can be calculated separately for each subject, cumulative for all subjects or by subject groups. This allows to compare subjects with healthy vision to a low vision patient group or to compare the viewing behavior of different age groups. Adaptive filters are provided to select the desired grouping and individual recordings can be included or excluded from the visualization and analysis process.

3.2 Fixation and Saccade Identification

One of the earliest and most frequent analysis steps is the identification of fixations and saccades. Their exact identification is essential for the calculation of many scan pattern characteristics, such as the average fixation time or saccade length.

Eye-tracking manufacturers often offer the possibility to identify fixations and saccades automatically. However, this filter step is not as trivial as the automated annotation may suggest. In fact, different algorithms yield quite different results. By offering a variety of calculation methods and making their parameters available for editing, we want to bring to mind the importance of the right choice of parameters. Especially when it comes to identifying the exact first and last point that still belong to a fixation and the merging of subsequent fixations that come to fall to the same location, relevant differences between algorithms and a high sensitivity to parameter changes can be observed.

As of now, algorithms of the following categories are implemented: spatial threshold-based approaches with minimum fixation duration and maximum spread, velocity-threshold and a Gaussian mixture model (Tafaj et al., 2012) that adaptively learns from the data and does not require any thresholds to be set.

Standard Algorithm

The standard algorithm for separating fixations and saccades is based on three adjustable values: The minimum duration of the fixations, the maximum radius of the fixations and the maximum number of points that are allowed to be outside this radius (helpful with noisy data). A time window of the minimum fixation duration is shifted over the measurement points until the conditions of maximum radius and maximum outliers are fulfilled. In the following step the beginning fixation is extended if possible until the number of allowed outliers has been reached. A complete fixation has been identified and the procedure starts anew. Every measurement point that was not assigned to a fixation is assigned to the saccade between its predecessor and successor fixation.

Velocity Based Algorithm

Since saccades show high eye movement speed while fixations and smooth pursuit movements are much slower, putting a threshold on the eye movement speed is a straight forward way of fixation filtering. *Eyetrace2014* currently implements three different variants of velocity based fixation identification. Each of the methods can filter short fixations via a minimum duration in a post-processing step.

Velocity Threshold by Pixel Speed [px/s]. A simple threshold over the speed between subsequent measurements. If the speed is exceeded, the measurement belongs to a saccade, otherwise to a fixation. While a pixel per second threshold is easy to interpret for the computer, it is often not meaningful to the experimenter and therefore hard to choose.

Velocity Threshold by Percentile. Based on the assumption that the velocity is bigger within saccades than within fixations, velocities are sorted by magnitude and a threshold is chosen by a percentile of the data selected by the user (usually 80-90%).
An example of sorted distances between measurements:
1 3 7 11 12 13 18 21 21 22
Green distances are supposed to belong to fixations for a 60% percentile (6 out of 10 distances) and the value 18 would be chosen as velocity threshold.

Velocity Threshold by Angular Velocity [/s]. This is the representation most common in the literature since it is independent of pixel count and individual viewing behavior. However, it also requires most knowledge about the data recording process in order to be able to convert the pixel distances into angular distances (namely the distance between viewer and screen, screen width and resolution). Suggested values for individual tasks can be found in the literature (Blignaut, 2009; Salvucci and Goldberg, 2000)

Gaussian Mixture Model

A Gaussian mixture model as introduced in (Tafaj et al., 2012) is also available. This method is based on the assumption that distances between subsequent measurement points within a fixation form a Gaussian distribution. Furthermore distances between measurement points that belong to a saccade also form a Gaussian distribution, but with different mean and standard deviation. A maximum likelihood estimation of the parameters of the Mixture of Gaussians is performed. Afterward for each measurement point the probability that it belongs to a fixation or to a saccade can be calculated and fixation/saccade labels are assigned based on these probabilities (Figure 2). The major advantage of this approach is that all parameters can be derived from the data. One could evaluate data recorded during an unknown experiment without the need to specify any thresholds or experimental conditions. The method has been evaluated in several studies (Kasneci et al., 2014a; Kasneci et al., 2015).

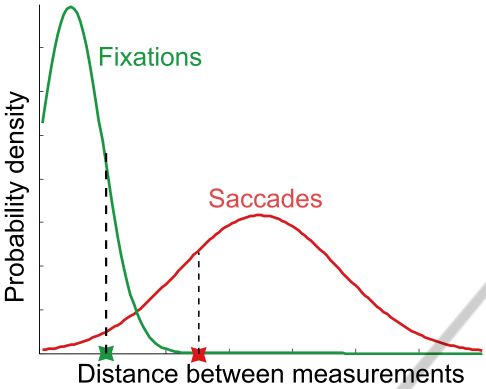


Figure 2: Fit of two Gaussian distributions to the large distances between subsequent measurements within saccades and the short distances between fixations. Two sample points are shown, one with higher probability to belong to a fixation (left) and one with a higher probability for a saccade (right).

3.3 Fixation Clustering

After identification of fixations and saccades the fixations can also be clustered. Areas with a high density of fixations are likely to contain semantically relevant objects. Clustering fixations either by neighborhood thresholds or mean-shift clustering (as proposed by (Santella and DeCarlo, 2004)) results in data-driven, automatically assigned areas of interest. This step reduces time consuming manual annotation and enables data analysis without prior knowledge of the analyst influencing the results (Figure 4).

Clusters of saccades correspond to frequent paths taken by the eyes. Fixation and saccade clusters can be calculated on the scan patterns of one subject or cumulative on a group of subjects.

Standard Clustering Algorithm
This greedy algorithm requires the definition of a minimum number of fixations that will be considered a cluster and the maximum radius of a cluster. Fixations are sorted in descending order of the number of included gaze points. Starting with the longest fixation, the algorithm iterates over all fixations, checking whether they fulfill the conditions of building a cluster with the biggest one. If the number of found fixations is sufficient, all found fixations are assigned to the same cluster and excluded from further clustering. If not, the first fixation cannot be assigned to any cluster and the algorithm starts again from the second longest fixation.

Mean-shift Clustering
The mean-shift clustering method assumes that measurements are sampled from Gaussian distributions around the cluster centers. The algorithm converges towards local point density maxima. The iterative procedure is shown in Figure 3. One of the main advantages is that it does not require the expected number of clusters in advance but determines an optimal clustering based on the data.

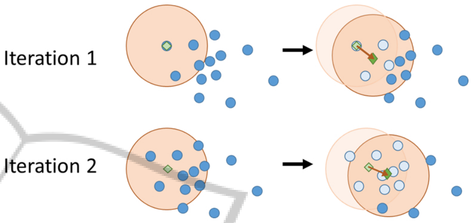


Figure 3: Simplified visualization of the mean-shift algorithm for the first two iterations at one starting point. In each iteration the mean (green square) of all data points (blue circles) within a certain window around a point (big red circle) is calculated. In the next iteration the procedure is repeated with the window shifted towards the previous mean. This is done until the mean convergence.

Cumulative Clustering
The clustering algorithms mentioned above can also be used on the cumulative data of more than one subject or more than one experiment condition. This way cumulative population clusters can be formed. They are more robust to noise and individual viewing behavior differences. The parameters of the algorithms are adapted for cumulative usage (e.g. the number of minimum fixations for the standard algorithm depends on the number of data sets used for cumulative analysis), but the way the methods work remain the same.

3.4 Areas of Interest (AOIs)

For the evaluation of specific regions, *Eyetrace2014* provides the possibility to annotate AOIs manually or by automatic conversion of fixation clusters. While the automated way is comfortable, the generated AOIs are not required to intuitively make sense. Annotating semantically meaningful areas is still done best by a human. Therefore we provide a graphical editor where polygonal AOIs can be defined and edited with few mouse clicks. Figure 4 shows an example of manually and automatically defined AOIs and also visualizes that automatically generated AOIs tend to - but do not necessarily - correspond to interesting regions of the image. All generated AOIs can be saved to disk and reused in other sessions or programs.

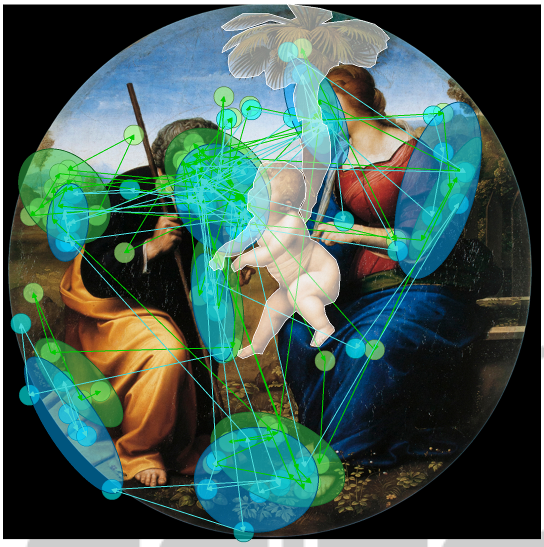


Figure 4: Simultaneous overlay of multiple visualization techniques for one scanpath of an image viewing task. The background image is shown together with a scanpath representation of fixed-size fixation markers (small circles) and generated fixation clusters (bigger ellipses) for left (green) and right (blue) eye. AOIs were annotated by hand (marked as white overlay).

3.5 Scanpath Comparison

Various characteristics of the scanpaths such as fixation durations and saccade lengths, as well as visual attention distribution and glance proportion towards fixation clusters can be calculated and exported. In addition to these global time-integrated scanpath descriptors, it is also possible to automatically compare scanpaths to each other. We therefore implemented a variant of ScanMatch (Cristino et al., 2010) that makes use of the fixation clusters and areas of interest described above. Fixation clusters are used in order to label the scanpath data (Santella and DeCarlo, 2004). ScanMatch then tries to align the fixation sequences by the Needleman-Wunsch string alignment algorithm.

We are planning to extend the scanpath comparison capabilities with automated image segmentation and object tracking functionality for AOI annotation as well as probabilistic scanpath comparison metrics.

4 DATA VISUALIZATION

The software allows simultaneous visualization of multiple scanpaths. These may represent different subjects, subject groups or distinct experiment conditions. The scan patterns are rendered in real-time as an overlay to an image or video stimulus. Various customizable visualization techniques are available: Fixations that encode fixation duration in their circular size, elliptical approximations encoding spatial extend as well as attention and shadow maps. Exploratory data analysis can be performed by traversing through the time dimension of the scan patterns as if it was a video. Most of the visualizations are interactive so that placing the cursor over the visualization of e. g. a fixation gives access to detailed information such as its duration and onset time.

4.1 Fixations and Fixation Clusters

The visualization of fixations and fixation clusters has to account for their spatial and temporal information. It is common to draw them as circles of either uniform size or to encode the fixation duration as the circle diameter. Besides these options, *Eyetrace2014* offers an ellipse fit visualization to the spatial extend of the fixation. The eigenvectors of all measurement points assigned to the fixation are calculated. These vectors point into the direction of highest variance within the data (see Figure 5). This visualization is especially useful when evaluating fixation filters and their parameters. We found it interesting and important to see that the jitter within a fixation does often not form a circular, but a stretched ellipse.

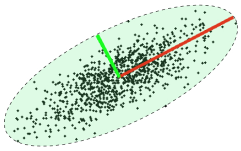
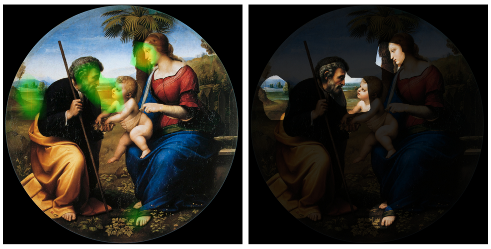


Figure 5: The two eigenvectors of Gaussian distributed samples (that correspond to the directions of highest variance). These are used as the major and minor axes for an elliptic fit.

4.2 Attention and Shadow Maps

Attention maps are one of the most common eyetracking analysis tools, besides the high number of subjects that have to be measured in order to get reliable results (Pernice and Nielsen, 2009). In order to enable fast attention map rendering even for a large number of recordings and high resolution, the attention map calculation utilizes multiple processor cores. Attention maps can be calculated for gaze points, fixations and fixation clusters. We provide the classical red-green color palette for attention maps as well as blue version for color-blind persons.

For the gaze point attention map each gaze point contributes as a two dimensional Gaussian distribution. The final attention map is then the sum over



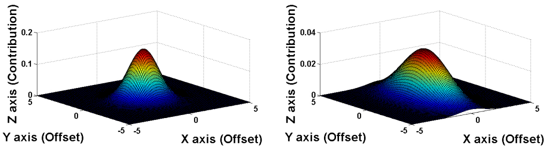
(a) (b)

Figure 6: An attention map calculated for fixation clusters (a) and the corresponding shadow map (b).

all Gaussians. The Gaussian distribution is specified by the two parameters size and intensity which are adjustable by the user. This Gaussian distribution is circular because gaze points do not have information about orientation and size. For fixations and fixation clusters the elliptic fit is used to determine the shape and orientation of the Gaussian distribution. Figure 7 shows an example of a circular Gaussian distribution (a) and a stretched, elliptical one (b).

$$P(x,y) = \frac{1}{\sigma_1 \sigma_2 2\pi\sqrt{1-\rho}} e^{-\frac{1}{2(1-\rho^2)}\left(\frac{x^2}{\sigma_1^2}+\frac{y^2}{\sigma_2^2}-\frac{2\rho xy}{\sigma_1\sigma_2}\right)} \quad (1)$$

Equation 1 shows the Gaussian distribution in the two dimensional case. σ_1 and σ_2 are the variance in horizontal and vertical direction respectively (see Figure 7). x and y are the offsets to the center of the Gaussian distribution (see Figure 7). The correlation coefficient ρ is zero in Figure 7 to simplify the case.



(a) (b)

Figure 7: Two Gaussian distribution calculated with $\sigma_1 = \sigma_2 = 1$ (a) and $\sigma_1 = 1$ and $\sigma_2 = 5$ (b).

A variant of the attention map is the shadow map that reveals only areas that were looked at (see Figure 6(b)). Its calculation is identical to that of the attention map with the difference of a smoothing step in order to show the border regions with higher sensitivity. This is done by calculating the n-th root of each map value where n is a user-defined parameter that regulates the desired smoothing.

4.3 Saccades

Saccades are typically visualized as arrows or lines connecting two fixations.

Besides this, a statistical evaluation can be visualized as a diagram called anglestar. It consists of a number of slices and a rotation offset. A slice of the anglestar codes in its length the number of saccades with the same angular orientation as the slice (e.g. if the slice represents the angles between 0° and 45° the number of saccades within that angle range contribute to that slice) to the horizontal axis is considered. The extend of a slice from the center of the star can represent the quantity, summed length or summed duration of the saccades towards that direction. Figure 8 shows a diagram where the extension of the slices is based on the summed length of the saccades.

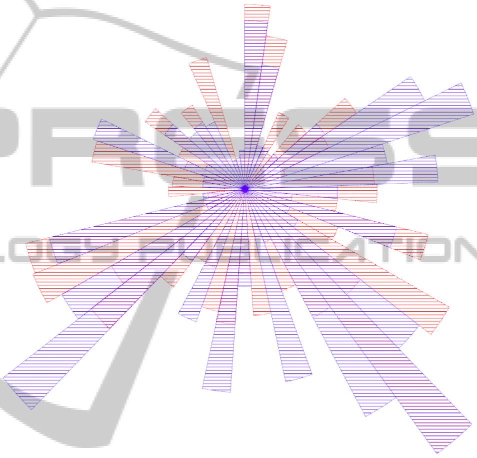


Figure 8: Representation of an anglestar, the red part represents data of the left eye, the blue part refers to data of the right eye.

4.4 AOI Transitions Diagram

For some evaluation cases it is interesting in which sequence attention is shifted between different areas. The AOI transitions diagram (Fig. 9) visualizes the transition probabilities between AOIs during a specific time period. The color of the transition is inherited from the AOI with most outgoing saccades. Hovering the mouse over an AOI shows all transitions from this AOI and hides the transitions from all other AOIs. Hovering the cursor over a specific transition displays an information box containing the number of transitions in both directions. Figure 9(b) e.g. shows that after watching AOI *cluster3* in more than 80% of cases gaze stayed at *cluster3*, in some cases gaze moved on towards *cluster1* or *cluster2* and in very few cases towards *cluster4* and *cluster5*.

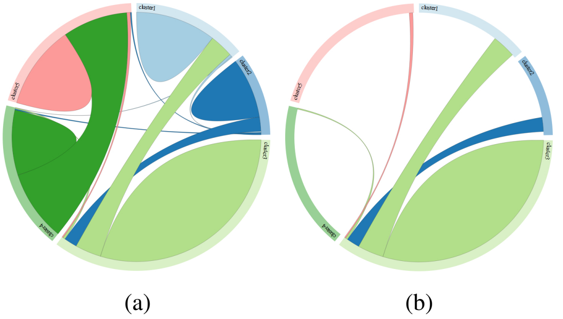


Figure 9: Diagram of the transitions between AOIs. The graphic is interactive and can blend out irrelevant edges if one AOI is selected (b).

5 DATA EXPORT

5.1 Statistics

General Statistics
Independent of all other calculations it is possible to calculate some general gaze statistics. These include the horizontal and vertical gaze activity, minimum, maximum and average speed of the gaze. These statistics shine a light on the agility and exploratory behavior of the subjects and can be exported in a format ready to use in statistical programs such as JMP or SPSS.

AOI Statistics
Numerous gaze characteristics can be calculated for AOIs, such as the total number of glances towards the AOI, the time of the first glance, glance frequency, total glance time, the glance proportion towards the AOI in respect to the whole recording and the minimum, maximum and mean glance duration. These statistics are a supplement to the AOI transitions diagram and can also be exported.

5.2 Visualization

The transition diagram as well as every visualization can be exported either loss-less as vector graphics or as bitmaps (png, jpg). *Eyetrace2014* provides the option to export the information about the subject (e.g. age, dominant eye) and the parameters used for calculation and visualization as a footer in the exported image. That way results can be reproduced and understood based solely on the exported image.

5.3 Evaluation Results

After calculating fixations, fixation clusters or cumulative clusters *Eyetrace2014* provides the possibility to export them as a text file.

Fixations are exported in a table including the running number, the number of included points, x and y coordinate, radius and if calculated the id of the cluster this fixation belongs to. The text file for the clusters and cumulative clusters include an ID number, the number of fixations contained, mean x, mean y and the radius.

Besides the already mentioned text files, fixations saccades and measurement error sections can be exported in order to allow extensive further processing in statistics programs, choosing the export option ”export events”.

6 CONCLUSION AND OUTLOOK

Summarizing our work of the last year and a half we believe that *Eyetrace2014* is a well structured program, advantageous enough to use it for university research but with its convenient handling nonetheless usable for persons without broad eye tracking experience, e.g. for teaching students. The major advantages of the software are the flexibility of algorithms and their parameters as well as their actuality in respect to the state of the art.

Eyetrace2014 has already been employed in several research projects, ranging from the viewing of fine art recorded via a static binocular SMI infrared eye-tracker to on-road and simulator driving experiments (Kasneci et al., 2014b; Tafaj et al., 2013) and supermarket search tasks (Sippel et al., 2014; Kasneci et al., 2014c) recorded via a mobile Ergoneers Dikablis tracker.

Nevertheless there are many plans to extend the *Eyetrace* software bundle in the next versions.

Besides the mandatory implementation of new eye tracker models to *EyetraceButler* we will extend the quality-check possibilities for the *EyetraceButler* plug-ins.

We want to extend the general and AOI based statistics calculations, add new calculation or visualization algorithms and make the existing ones more interactive and transparent. A special focus will be given the analysis and processing of saccadic eye movements as well as to the automated annotation of AOIs for dynamic scenarios (Kübler et al., 2014) and non-elliptical AOIs.

We plan on including further automated scanpath comparison metrics, such as MultiMatch (Dewhurst et al., 2012) or SubsMatch (Kübler et al., 2014).

Another relevant area is the monitoring of vigilance and workload during the experiment. Especially for medical applications such as reaction or stimulus sensitivity testing the mental state of the subject is of importance. Available data such as the pupil dilation, fatigue waves (Henson and Emuh, 2010), saccade length differences (Di Stasi et al., 2014) and blink rate may give important insight into the data and even yield e.g. cognitive workload weighted attention maps.

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