FixaTons: A collection of Human Fixations
Datasets and Metrics for Scanpath Similarity

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1 Introduction

In the last three decades, human visual attention has been a topic of great interest in various disciplines. In computer vision, many models have been proposed to predict the distribution of human fixations on a visual stimulus. Recently, thanks to the creation of large collections of data, machine learning algorithms have obtained state-of-the-art performance on the task of saliency map estimation.

On the other hand, computational models of scanpath are much less studied. Works are often only descriptive \cite{1} or task specific \cite{2}. This is due to the fact that the scanpath is harder to model because it must include the description of a dynamic. General purpose computational models are present in the literature, but are then evaluated in tasks of saliency prediction \cite{3}, losing therefore information about the dynamics and the behaviour. In addition, two technical reasons have limited the research. The first reason is the lack of robust and uniformly used set of metrics to compare the similarity between scanpath. The second reason is the lack of sufficiently large and varied scanpath datasets.

In this report we want to help in both directions. We present FixaTons, a large collection of datasets human scanpaths (temporally ordered sequences of fixations) and saliency maps. It comes along with a software library for easy data usage, statistics calculation and implementation of metrics for scanpath and saliency prediction evaluation.

2 Datasets included in the collection

FixaTons is a collection of publicly available datasets of human fixations. The authors of this paper have also included SIENA12, which is a further set of grayscale images that aim at being as more free of semantic content as possible.

2.1 SIENA12

The SIENA12 dataset includes 12 grayscale images\footnote{The authors thank Danilo Pileri for kindly providing images of the dataset.}. It was collected by the author of this paper in collaboration with EVALAB at Policlinico Alle Scotte in Siena. The images have been selected so as to minimize the semantic content of the scenes. Images include natural scenes, human constructions, but also abstract contents.

2.1.1 Protocol for data collection in SIENA12

Visual data are collected through a 240 Hz eye-tracking system (ASL 504, Applied Science Laboratories, Bedford, MA, USA) allowing for a remote tracking of the point of gaze on a calibrated surface (LCD screen, 1024 × 768 px, 31 × 51 cm). A chin-rest is used to maintain constant the relative distances between the eyes of the subject, the eye-tracker optics and the screen (eye/eye-trackers distance, 68 cm; eye/screen distance, 72 cm). The height of the chin-rest is set in order to get the line of sight of the subjects at the rest position.
perpendicular to the centre of the screen. The stimuli presentation and the data collection is managed by customized software. All recordings are conducted in complete darkness, measuring one eye.

A nine-point calibration is performed through an interactive user interface provided by the manufacturer. The operator instructs the participant to perform 5 seconds tasks of free visual exploration. A total of 12 images is presented. Between one image and another, a central dot (of about 2 seconds) is displayed. The order of the images composing the sequence of the experimental stimuli is randomly chosen to prevent bias.

Raw data has been processed with the publicly available python library PyGazeAnalyser [4] in order to extract information about fixations.

| Dataset Name  | SIENA12             |
|---------------|----------------------|
| Number of images | 12                  |
| Size          | 1024x768 px          |
| Categories    | Outdoor, natural, synthetic |
| Number of observers | 23                 |
| Age of the observers | From 23 to 52     |
| Task          | Free-viewing        |
| Duration      | 5 seconds           |
| Eye-tracker   | ASL 504 (240 Hz)    |
| Screen        | LCD 1024 × 768 px (31 × 51 cm) |
| Eye-screen distance | 72 cm               |
| Other information | Grayscale images    |

Table 1: Tech. spec. of the dataset SIENA12
2.2 Other Datasets

Authors of compatible datasets are encouraged to add them to this collection. Please, send an email to the corresponding author of this report along with an authorization to redistribute that data. Below, the list of datasets currently added to the collection.

2.2.1 MIT1003

The dataset MIT1003 is a large database of eye tracking data. The images, eye tracking data, and accompanying code in Matlab are all available on the web. This dataset can be used as training data for the MIT300 benchmark since they share the same technical specification. MIT300 is not included in FixaTons collection because its data is kept private for a fair evaluation of the benchmark. More details about the protocol used for data collection are given in the referred paper.
| Dataset Name   | MIT1003                        |
|----------------|--------------------------------|
| Number of images | 1003                          |
| Size            | Min. dim.: 405 px – Max. dim.: 1024 px |
| Categories      | Landscape and portrait images  |
| Number of observers | 15                            |
| Age of the observers | From 18 to 35            |
| Task            | Free-viewing                  |
| Duration        | 3 seconds                     |
| Eye-tracker     | ETL 400 ISCAN (240Hz)         |
| Screen          | LCD 1024 × 768 px (40.5 × 30 cm) |
| Eye-screen distance | 75 cm                        |
| Other information | It can be used as training data for MIT300 benchmark |

Table 2: Tech. spec. of the dataset MIT1003

3 Online resources

- Webpage of the project: [http://sailab.diism.unisi.it/fixatons/](http://sailab.diism.unisi.it/fixatons/)
- Data download: [https://drive.google.com/open?id=1TQSaq5J0p_oDkYVZ-IzBlJwJ2cm3UA](https://drive.google.com/open?id=1TQSaq5J0p_oDkYVZ-IzBlJwJ2cm3UA)
- Software library [https://github.com/dariozanca/FixaTons](https://github.com/dariozanca/FixaTons)
4 Structure of the FixaTons collection

- FixaTons
  - DATASET_NAME
    - STIMULI: contains original images. They can have different file format (jpg, jpeg, png,...)
    - SCANPATHS: contains one folder for each image
      - IMAGE_ID: it contains one file for each scanpath of that image scanpaths. All rows of this matrix describe fixations; each fixation is of the form: [x-pixel, y-pixel, initial time, final time]. Times are in seconds.
    - FIXATION_MAPS: contains a fixation map of each original image. They are matrices of zeros (non-fixated pixels) and ones (fixated pixels). They can have different file format (jpg, jpeg, png,...)
    - SALIENCY_MAPS: contains saliency maps of each original image. They are generated from human data. They can have different file format (jpg, jpeg, png,...)

5 Software included

Some software tools are provided together with the collection for an easy use and visualization of the data.

Software is written in python. All the functions are included in the file FixaTons.py. They make use of the public library OpenCV which should be installed on the machine before the use of FixaTons.py.

Functions can be divided in five main categories:

- List information
- Get data (matrices)
- Visualize data
- Compute metrics.
- Compute statistics

5.1 List information

The collection comprehend different datasets, each of them with different stimuli names, number of subjects, subjects id’s, etc. The provided software allows to easily get this kind of information.
• **FixaTons.list.dataset()**: This function returns a list with the names of the datasets included in the collection.

• **FixaTons.list.stimuli(DATASET_NAME)**: This function lists the names of the stimuli of a specified dataset.

• **FixaTons.list.subjects(DATASET_NAME, STIMULUS_NAME)**: This function lists the id’s of the subjects which have been watching a specified stimuli of a dataset.

5.2 Get data (matrices)

Different functions allow to get data in form of numpy array.

• **FixaTons.get.stimulus(DATASET_NAME, STIMULUS_NAME)**: This function returns the matrix of pixels of a specified stimulus. Notice that, both DATASET_NAME and STIMULUS_NAME need to be specified. The latter, must include file extension. The returned matrix could be 2- or 3-dimensional.

• **FixaTons.get.fixation_map(DATASET_NAME, STIMULUS_NAME)**: This function returns the matrix of pixels of the fixation map of a specified stimulus. Notice that, both DATASET_NAME and STIMULUS_NAME need to be specified. The latter, must include file extension. The returned matrix is a 2-dimensional matrix with 1 on fixated locations and 0 elsewhere.

• **FixaTons.get.saliency_map(DATASET_NAME, STIMULUS_NAME)**: This function returns the matrix of pixels of the saliency map of a specified stimulus. Saliency map has been obtained by convolving the fixation map with a proper gaussian filter (corresponding to one degree of visual angle). Notice that, both DATASET_NAME and STIMULUS_NAME need to be specified. The latter, must include file extension. The returned matrix is a 2-dimensional matrix.

• **FixaTons.get.scanpath(DATASET_NAME, STIMULUS_NAME, subject = 0)**: This function returns the matrix of fixations of a specified stimulus. The scanpath matrix contains a row for each fixation. Each row is of the type \([x, y, initial\_t, final\_time]\). By default, one random scanpath is chosen between available subjects. For a specific subject, it is possible to specify its id on the additional argument subject=id.

5.3 Visualize data

For an easy visualization of the data, some functions have been included in the library.

• **FixaTons.show.map(DATASET_NAME, STIMULUS_NAME, showSalMap = True, showFixMap = False, plotMaxDim = 0)**: This function uses cv2 standard library to visualize a specified stimulus. By default, stimulus is shown with its
saliency map aside. It is possible to deactivate such option by setting the additional argument showSalMap=False. It is possible to show also (or alternatively) the fixation map by setting the additional argument showFixMap=True. Depending on the monitor or the image dimensions, it could be convenient to resize the images before to plot them. In such a case, user could indicate in the additional argument plotMaxDim=500 to set, for example, the maximum dimension to 500. By default, images are not resized.

- **FixaTons.show.scanpath(DATASET_NAME, STIMULUS_NAME, subject = 0, animation = False, putNumbers = True, plotMaxDim = 0)**: This functions uses cv2 standard library to visualize the scanpath of a specified stimulus. By default, one random scanpath is chosen between available subjects. For a specific subject, it is possible to specify its id on the additional argument subject=id. It is possible to visualize it as an animation by setting the additional argument animation=True. Depending on the monitor or the image dimensions, it could be convenient to resize the images before to plot them. In such a case, user could indicate in the additional argument plotMaxDim=500 to set, for example, the maximum dimension to 500. By default, images are not resized.

5.4 Compute metrics

An implementation of the most common metrics to compute saliency maps similarity and scanpaths similarity is included in the software provided with FixaTons. A mathematical description of the metrics of scanpath similarity is postponed to the Appendix.

- **Saliency Map similarities**
  - **FixaTons.metrics.KLdiv(saliencyMap1, saliencyMap2)**: This function computes the Kullback–Leibler divergence between two continuous saliency maps.
  - **FixaTons.metrics.AUC_Judd(saliencyMap, fixationMap, jitter = True, toPlot = False)** Given a continuous saliency map (normally the output of a saliency model) and a fixation map (matrix with 1’s at fixated locations, 0’s elsewhere), it computes the Area Under the ROC curve, in the implementation described by Judd in [5].
  - **FixaTons.metrics.NSS(saliencyMap, fixationMap)** Given a continuous saliency map (normally the output of a saliency model) and a fixation map (matrix with 1’s at fixated locations, 0’s elsewhere), it computes the Normalized Scanpath Saliency

- **Scanpaths similarities**
  - **FixaTons.metrics.euclidean_distance(human_scanpath, simulated_scanpath)**: This function computes the euclidean distance between two scanpaths. More details are given on the Appendix.
- FixaTons.metrics.string_edit_distance(stimulus, human_scanpath, simulated_scanpath, n = 5, substitution_cost=1): This function computes the string-edit distance between two scanpaths. More details are given on the Appendix.

- FixaTons.metrics.time_delay_embedding_distance( human_scanpath, simulated_scanpath, k = 3, distance_mode = 'Mean'): This function computes the time-delay embedding distance between two scanpaths. More details are given on the Appendix.

- FixaTons.metrics.scaled_time_delay_embedding_distance( human_scanpath, simulated_scanpath, image, toPlot = False)): This function computes the scaled time-delay embedding distance between two scanpaths. More details are given on the Appendix.

5.5 Compute statistics

It is possible to compute statistics for the overall collection, or for a specific dataset, about some scanpath properties.

- FixaTons.stats.statistics(DATASET_NAME=None): This function returns a list with two values: fixations per second and the average of saccades length. If no dataset is specified, statistics are calculated on the whole FixaTons collection. To restrict computation on a specific dataset, it is sufficient to indicate its name on the additional argument DATASET_NAME.

5.6 Example of use

Here we propose a python script which show a complete example of use of some facilities.

```python
# import the library
import FixaTons

# shuffle (dataset_list)
for dataset in FixaTons.list.datasets:
    # For all images in that dataset
    for image in FixaTons.list.stimuli(dataset):
        # Show the image aside its saliency map (5 seconds by default).
        FixaTons.show.map(dataset, image, plotMaxDim=1500)

        # Then, for all the subjects that watched that image,
        for subject in FixaTons.list.subjects(dataset, image):
            # Show the correspondent scanpath as an animation.
            # (Look, time of exploration in the animation is the
            # exact time, from the dataset.)
            FixaTons.show.scanpath(dataset, image, subject,
```


Listing 1: Example of use. Complete Python script.

6 Appendix A:

In this section we define metrics to compute similarity between scanpaths. Metrics of course work for given two sequences of point in the $\mathbb{R}^2$ plane, but for the sake of clearness, we will contextualize to our topic. Let say our goal is to compute a distance between a simulated and a human scanpath,

\[
s \equiv s(1), ..., s(n) \\
h \equiv h(1), ..., h(m)
\]

where

\[
s(i) \in \mathbb{R}^2, \forall i \in \{1, ..., n\}, \\
h(j) \in \mathbb{R}^2, \forall j \in \{1, ..., m\}.
\]

6.1 Euclidean distance

Let us suppose the two scanpaths $s$ and $h$ have the same length $n$. We define the Euclidean distance between two scanpath as the mean of the Euclidean distances between corresponding fixations. To give a mathematical formulation,

\[
d_{Euclidean}(s, h) = \frac{1}{n} \sum_{i=0}^{n} \|s(i) - h(i)\|_2
\] (1)

This metric presents some important drawbacks.

i. The two scanpaths has to have the same length, i.e. $n$ must be equal to $m$. But human scanpaths in the available collection of data rarely have same length, and to restrict to the minimum length would produce a huge loss of important data.

ii. Euclidean metric does not take time-shifts into account. Let us indicate fixation locations $s(i), h(i) \in \mathbb{R}^2, \forall i \in \{1, ..., n\}$, with capital letters. Then, the scanpaths ABCDEF and ZABCDE, even if very similar, would be very distant.
6.2 String-edit similarity

One of the most common metrics to compute scanpaths similarity is the "string-edit" or Levenshtein distance. The algorithm of the dynamic program to compute this metric is described in [7]. The metric has been used in different works for comparing different human scanpaths [9, 8]. It has been shown [10] to be robust to changes in the number of regions used.

Input stimulus is divided into n×n regions, labeled with characters. Scanpaths are turned into strings by associating the corresponding character to each fixation. Finally, the algorithm of string-edit is used to measure the distance between the two generated strings.

6.3 Time-delay embedding distance

Time-delay embedding are used in order to quantitatively compare stochastic and dynamic scanpaths of varied lengths. This metric is largely used in dynamic systems analysis and carefully described in [11]. In particular, let us consider the problem of comparing a simulated and a human scanpath, 

\[ \begin{align*}
  s &\equiv s(1), ..., s(n) \\
  h &\equiv h(1), ..., h(m)
\end{align*} \]

eventually of different length, \( n \neq m \). They are ordered list of fixations. Each fixation is defined by a couple of spatial coordinates (that correspond to the fixated location in the image), that is

\[ \begin{align*}
  s(i) &\in \mathbb{R}^2, \forall i \in \{1, ..., n\}, \\
  h(j) &\in \mathbb{R}^2, \forall j \in \{1, ..., m\}.
\end{align*} \]

We indicate with

\[ C^k_s(t) = (s(t), ..., s(t + k)) \]

a \( k \)-dimensional sub-sequence of fixation extracted from the simulated scanpath \( s \), starting from the \( t \)-th fixation, and with

\[ X = \{C^k_s(t)\}_{t \in \{1, ..., n-k\}} \subset \mathbb{R}^k \] \hspace{1cm} (2)

the space of all this possible \( k \)-dimensional sub-sequences extracted from \( s \). Analogously,

\[ C^k_h(t) = (h(t), ..., h(t + k)) \]

is a \( k \)-dimensional sub-sequence of fixation extracted from the human scanpath \( h \), starting from the \( t \)-th fixation, and

\[ Y = \{C^k_h(t)\}_{t \in \{1, ..., m-k\}} \subset \mathbb{R}^k \] \hspace{1cm} (3)
is the the space of all this possible $k$-dimensional sub-sequences extracted from $h$. Notice that $k < \min\{n, m\}$. Comparison between the clouds $X$ and $Y$ of data points in $\mathbb{R}^k$ will reflect dynamical similarities between the two scanpaths.

Given

$$d_k(x, Y) = \min_{y \in Y} \{\|x - y\|\},$$  

(4)

the time-delay embedding distance is then defined as the \textit{mean minimal} distance (MM-distance)

$$tdc_{MM}^k(s, h) = \frac{1}{|X|} \sum_{x \in X} d_k(x, Y)$$  

(5)

or as the Hausdorff distance (H-distance)

$$tdc_{H}^k(s, h) = \max_{x \in X} d_k(x, Y).$$  

(6)

### 6.4 Scaled Time-delay embedding distance

The distance based on the time-delay embedding described in the previous section allows to capture dynamics as well as stochastics aspects of the compared processes. The resulting metric is, however, given in pixel, since no re-scaling is applied anywhere. In real world datasets input may differ a lot in resolution. To take this into account, we define a scaled version of such a metric, where fixations coordinates are normalized in $[0, 1]^2$.

More specifically, let us consider the problem of comparing a \textit{simulated} and a \textit{human} scanpath over an image $I$, say

$$s \equiv s(1), \ldots, s(n)$$

$$h \equiv h(1), \ldots, h(m)$$

eventually of different length, $n \neq m$. They are ordered list of fixations. Each fixation is defined by a couple of spatial coordinates, that is

$$s(i) \in [0, l_1], \forall i \in \{1, \ldots, n\},$$

$$h(j) \in [0, l_2], \forall j \in \{1, \ldots, m\}.$$  

where $l_1$ and $l_2$ are, respectively, the horizontal and vertical dimensions of $I$. First, fixations coordinates are normalized in $[0, 1]^2$, dividing by maximum of the dimensions $L = \max\{l_1, l_2\}$, that is

$$\tilde{s}(i) = s(i)/L, \forall i \in \{1, \ldots, n\},$$

$$\tilde{h}(j) = h(i)/L, \forall j \in \{1, \ldots, m\}.$$
Now we notice that $tde$ depends on the choice of the sub-sequences lengths $k$. To obtain a single more comprehensive measure, we define the \textit{scaled time-delay embedding similarity} as

$$stde(s, h) = \exp \frac{1}{K} \sum_{k \in K} tde_k(s, h),$$

where $K = \{1, ..., \min\{n, m\} - 1\}$ is the set of all possible sub-sequences lengths. Notice that $stde(s, h) = 1$ indicates perfect similarity, while as it approaches zero the more dissimilar the scanpaths are.

\textbf{References}

[1] Lee, T. S., Stella, X. Y.: An information-theoretic framework for understanding saccadic eye movements. Advances in neural information processing systems, pp 834–840. (2000)

[2] Renninger, L. W., Coughlan, J. M., Verghese, P., Malik, J.: An information maximization model of eye movements. Advances in neural information processing systems, pp 1121–1128. (2005)

[3] Zanca, D., Gori, M.: Variational Laws of Visual Attention for Dynamic Scenes. Advances in Neural Information Processing Systems, pp 3826–3835 (2017)

[4] Dalmaijer, E.S., MathÃťt, S., Van der Stigchel, S.: PyGaze: an open-source, cross-platform toolbox for minimal-effort programming of eye tracking experiments. Behavior Research Methods, vol 46, pp 913–921 (2014)

[5] Judd, T., Ehinger, K., Durand, F., Torralba, A.: Learning to Predict Where Humans Look. IEEE International Conference on Computer Vision (2009)

[6] Judd, T., Durand, F., Torralba, A.: A Benchmark of Computational Models of Saliency to Predict Human Fixations. MIT Technical Report. (2012)

[7] Jurafsky, D., Martin, J. H.: Speech and Language Processing. London: Pearson. (2014)

[8] Brandt, S. A., Stark, L. W.: Spontaneous eye movements during visual imagery reflect the content of the visual scene. Journal of cognitive neuroscience, vol 9, n 1, pp 27–38. (1997)

[9] Foulsham, T., Underwood, G.: What can saliency models predict about eye movements? Spatial and sequential aspects of fixations during encoding and recognition. Journal of Vision, vol = 8, n = 2, pp 6. (2008)

[10] Choi, Y. S., Mosley, A. D., Stark, L. W.: String editing analysis of human visual search. Optometry and Vision Science, vol 72, pp 439–451. (1995)
[11] Wang, W., Chen, C., Wang, Y., Jiang, T., Fang, F., Yao, Y.: Simulating human saccadic scanpaths on natural images. Computer Vision and Pattern Recognition (CVPR), pp 441–448. (2011)