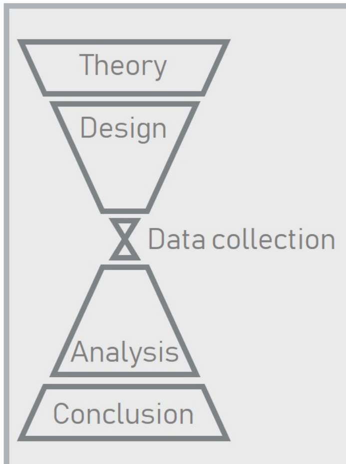
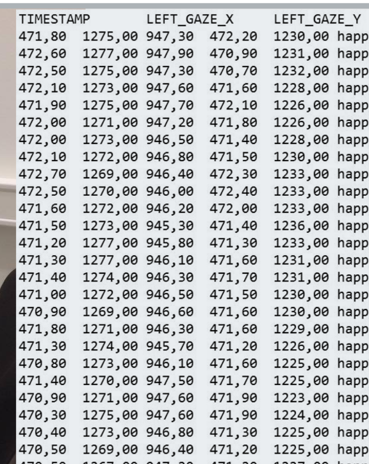
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

FACULTY OF SCIENCE

CLEMSON UNIVERSITY





TIMESTAMP		LEFT_GAZE_X		LEFT_GAZE_Y	
471,80	1275,00	947,30	472,20	1230,00	happy
472,60	1277,00	947,90	470,90	1231,00	happy
472,50	1275,00	947,30	470,70	1232,00	happy
472,10	1273,00	947,60	471,60	1228,00	happy
471,90	1275,00	947,70	472,10	1226,00	happy
472,00	1271,00	947,20	471,80	1226,00	happy
472,00	1273,00	946,50	471,40	1228,00	happy
472,10	1272,00	946,80	471,50	1230,00	happy
472,70	1269,00	946,40	472,30	1233,00	happy
472,50	1270,00	946,00	472,40	1233,00	happy
471,60	1272,00	946,20	472,00	1233,00	happy
471,50	1273,00	945,30	471,40	1236,00	happy
471,20	1277,00	945,80	471,30	1233,00	happy
471,30	1277,00	946,10	471,60	1231,00	happy
471,40	1274,00	946,30	471,70	1231,00	happy
471,00	1272,00	946,50	471,50	1230,00	happy
470,90	1269,00	946,60	471,60	1230,00	happy
471,80	1271,00	946,30	471,60	1229,00	happy
471,30	1274,00	945,70	471,20	1226,00	happy
470,80	1273,00	946,10	471,60	1225,00	happy
471,40	1270,00	947,50	471,70	1225,00	happy
470,90	1271,00	947,60	471,90	1223,00	happy
470,30	1275,00	947,60	471,90	1224,00	happy
470,40	1273,00	946,80	471,30	1225,00	happy
470,50	1269,00	946,40	471,20	1225,00	happy
470,50	1267,00	947,20	471,20	1227,00	happy

Workshop: Eye Tracking Data Analytic Pipeline

Nina Gehrer (University of Tübingen, Germany)
Andrew Duchowski (Clemson University, USA)

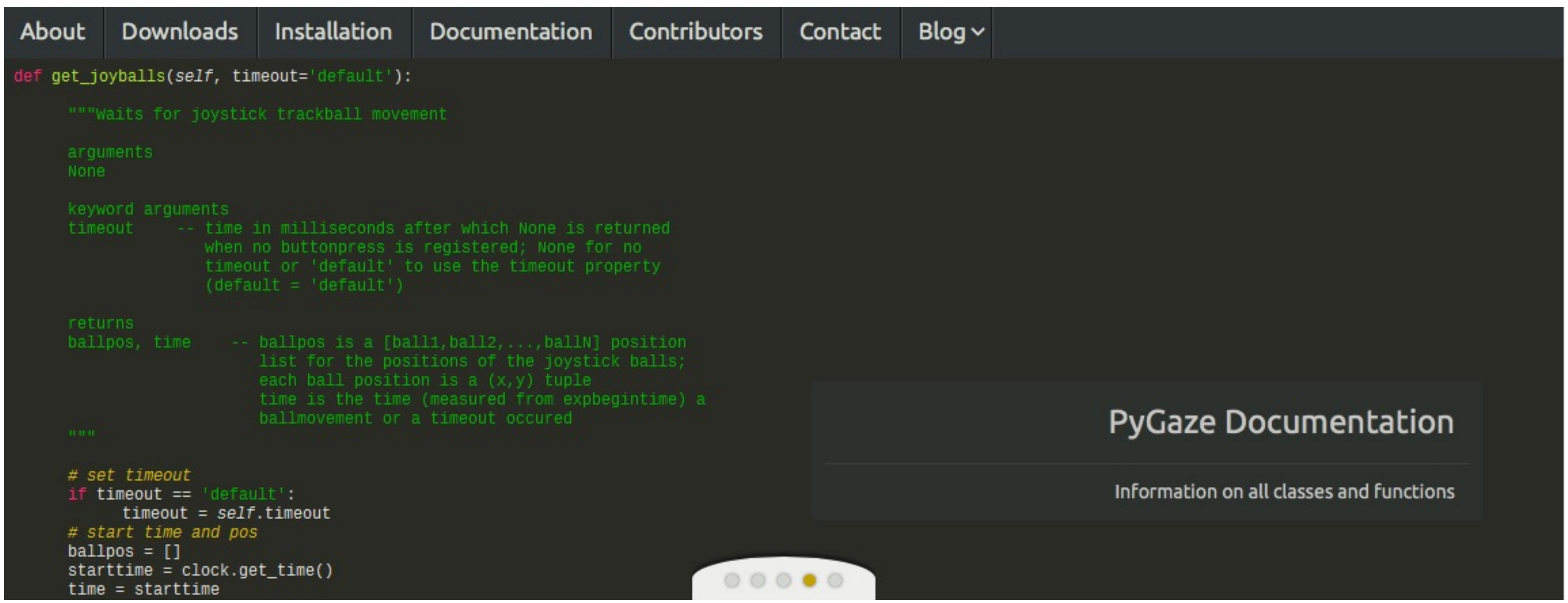
Gaze Analytics Pipeline: Origins

- What is it?
  - series of Python scripts followed by analysis in R
  - goal: automation

- How did it start, evolve?
  - ETH Winter School 2016

Gaze Analytics Pipeline: Ontology

- Where does it fit?
  - Note quite `PyGaze` (www.pygaze.org)

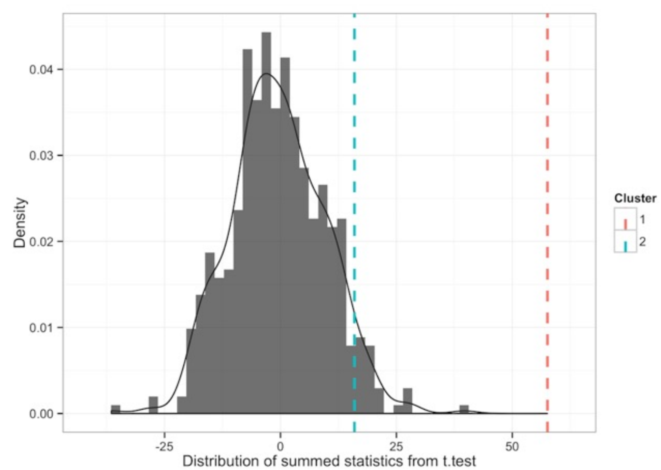


Gaze Analytics Pipeline: Ontology

- Where does it fit?
  - Note quite `eyetrackingR` (www.eyetracking-r.com)

What is *eyetrackingR*?

eyetrackingR is an R package designed to make dealing with eye-tracking data easier. It handles tasks along the pipeline from raw data to analysis and visualization -- as illustrated in the eyetrackingR workflow. Check out the vignettes to the left for some gentle introductions to using eyetrackingR for several popular types of analyses, including growth-curve analysis, onset-contingent reaction time analyses, as well as several non-parametric bootstrapping approaches.



Bootstrapped cluster analysis distribution plot

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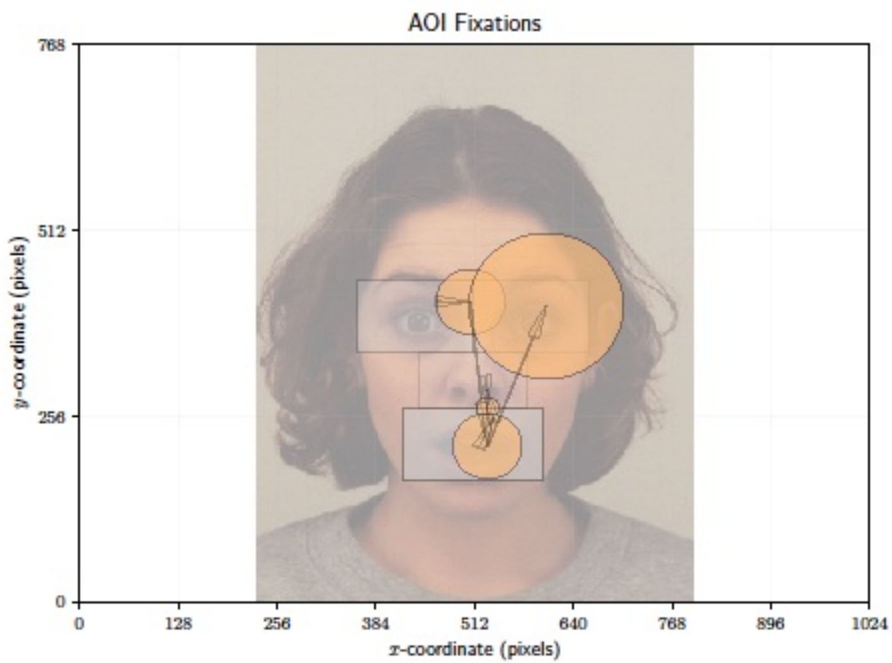
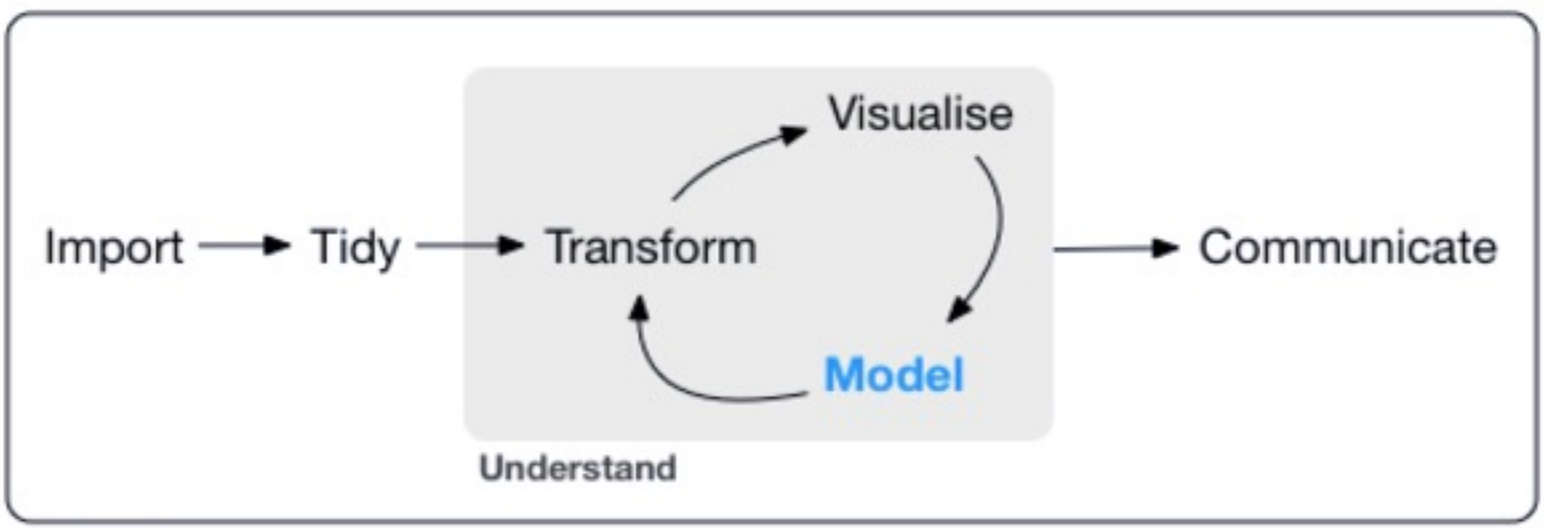
Gaze Analytics Pipeline: Objectives

- How does it work?
  - key goals: visualization and analysis



Gaze Analytics Pipeline: Objectives

- How does it work?
  - key goals: visualization and analysis
  - like R's *tidyverse*, sort of
  - idea is the same: import data, tidy, visualize, collate, analyze
  - each step a different Python script



Gaze Analytics Pipeline: Objectives

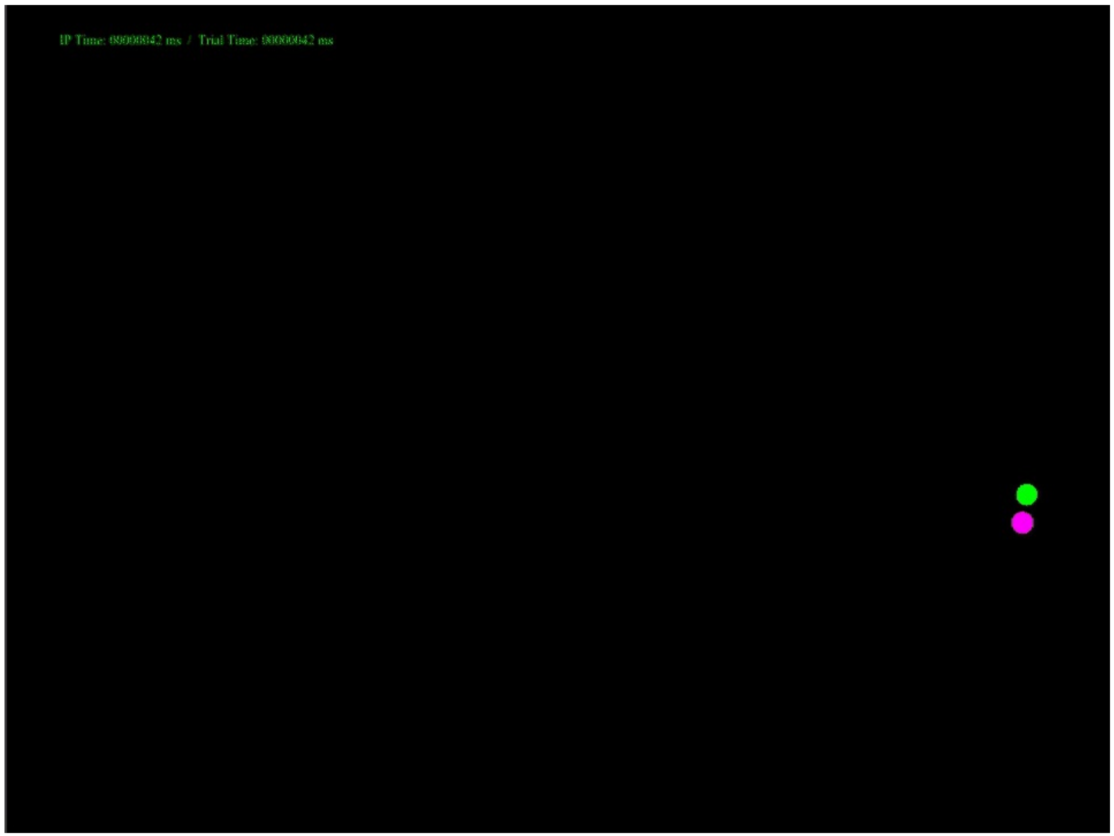
- How does it work?
  - key goals: visualization and analysis

Time Schedule

Part 1 (Hands-on)
- Introduction to file system structure (preparations) - Start running the python scripts - Experiment setup and analytics pipeline overview

Part 2 (Theory & Results)
- Traditional gaze analytics (working with R scripts) - Advanced gaze analytics

Emotion categorization paradigm



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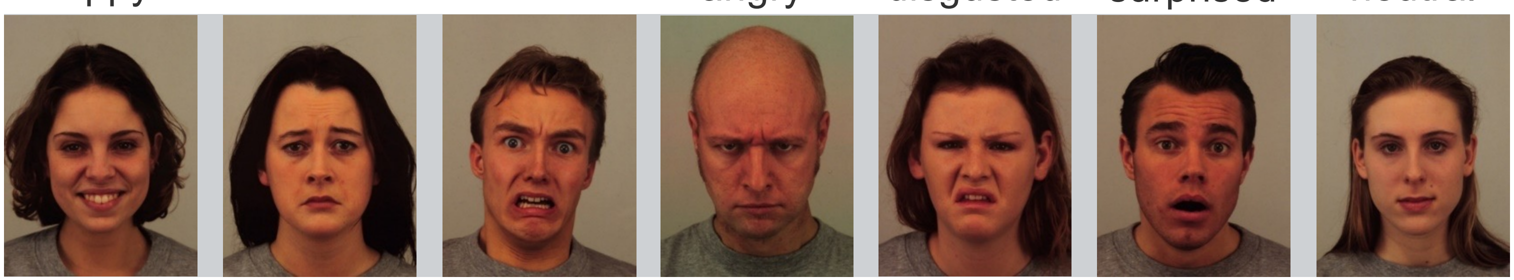
Emotion categorization paradigm

7 emotion categories → 16 trials per emotion → 112 trials (randomized, 2 blocks)

happy | sad | fearful | angry | disgusted | surprised | neutral



(Karolinska Directed Emotional Faces database; Lundqvist, Flykt, & Öhman, 1998)

Apparatus

- EyeLink 1000 Eye Tracker (SR Research)
- Measurement binocular at 500 Hz
- Screen size: 19 inch
- Screen resolution: 1024x768 pixels
- Screen distance: 60 cm
- 9-point calibration

Data

Participants: 24 students

SOR_es01mb.txt	18.01.2018 13:34	Textdokument	15.982 KB
SOR_es02te.txt	18.01.2018 13:34	Textdokument	16.179 KB
SOR_es03lb.txt	18.01.2018 13:34	Textdokument	16.260 KB
SOR_es05sk.txt	18.01.2018 13:34	Textdokument	15.928 KB
SOR_es06ss.txt	18.01.2018 13:34	Textdokument	16.260 KB
SOR_es07sg.txt	18.01.2018 13:34	Textdokument	16.261 KB
SOR_es09ls.txt	18.01.2018 13:34	Textdokument	16.405 KB
SOR_es10aw.txt	18.01.2018 13:34	Textdokument	15.984 KB
SOR_es13lg.txt	18.01.2018 13:34	Textdokument	16.458 KB
SOR_es14mh.txt	18.01.2018 13:34	Textdokument	16.222 KB

…

Data

Variables:

RECORDING_SESSION_LABEL	Group_VP	blocknr	trialnr
es01mb	stud	1	1
es01mb	stud	1	1
es01mb	stud	1	1

task	emotion	gender	face	dc_x	list
emotion	surprised	male	M08	80	1
emotion	surprised	male	M08	80	1
emotion	surprised	male	M08	80	1

TIMESTAMP	LEFT_GAZE_X	LEFT_GAZE_Y	LEFT_PUPIL_SIZE	RIGHT_GAZE_X	RIGHT_GAZE_Y	RIGHT_PUPIL_SIZE
2154988	78,1	463,2	1296	126	467,4	1205
2154990	77,8	464,1	1299	126,3	467,2	1204
2154992	79,3	464,5	1296	125,5	467	1202

RESPONSE	IS_CORRECT
surprised	Correct
surprised	Correct
surprised	Correct

Effect of facial emotional expression on traditional and advanced gaze analytics:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:
   - Absolute dwell time, number of fixations
   - Frequency of the initial fixation after stimulus onset
   - Number of transition between AOIs

2) Measures of scanning behavior in general:
   - Absolute number of fixations, duration of fixations
   - pICA
   - K coefficient (ambient / focal fixations)
   - Microsaccades (rate, amplitude)

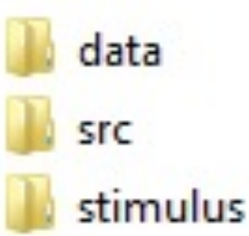
3) Transition matrices and transition entropy

traditional

advanced

Preparation for Analysis:

Structure of directories and files

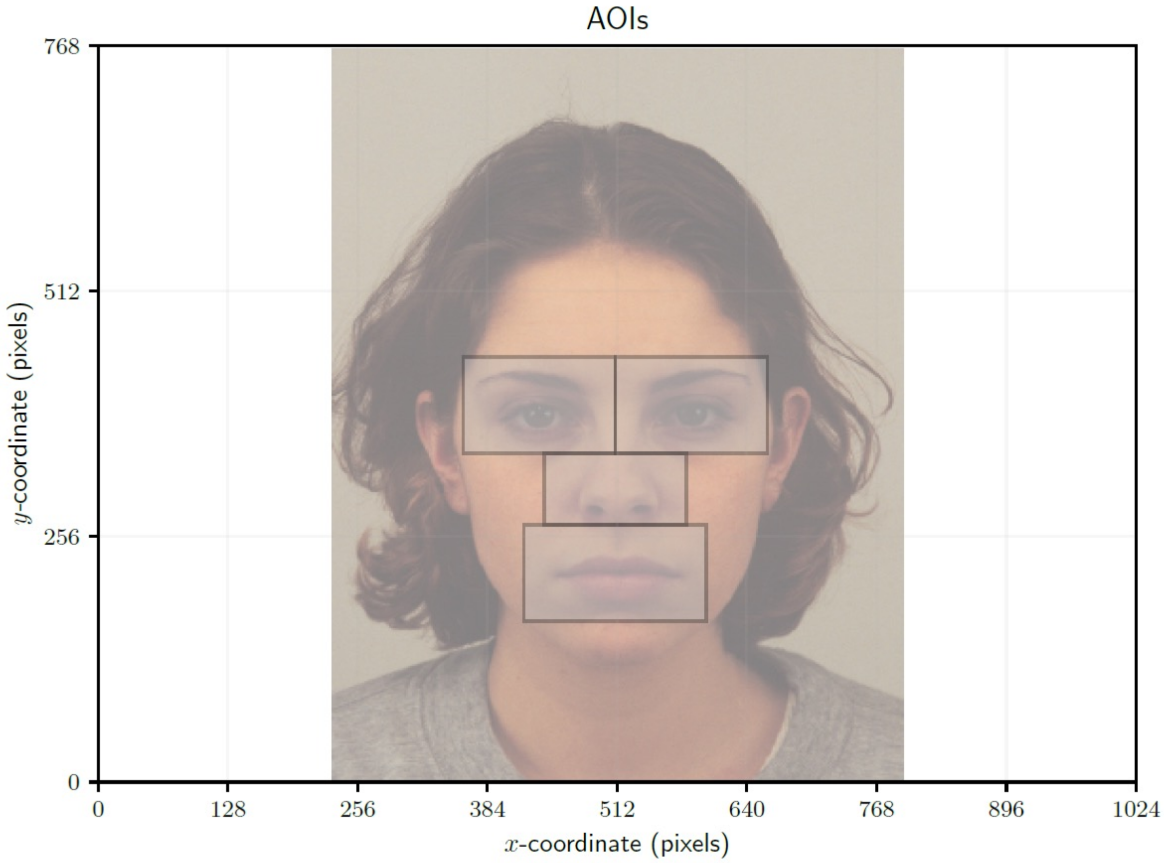


- Images of stimuli
- Data
- Information about data recording: Screen size and resolution, screen distance, etc.

Definition of AOIs in Scribus:
Left eye, right eye, nose, mouth

aoidefinition-2eyes-1024x768.sla

Preparation for Analysis:



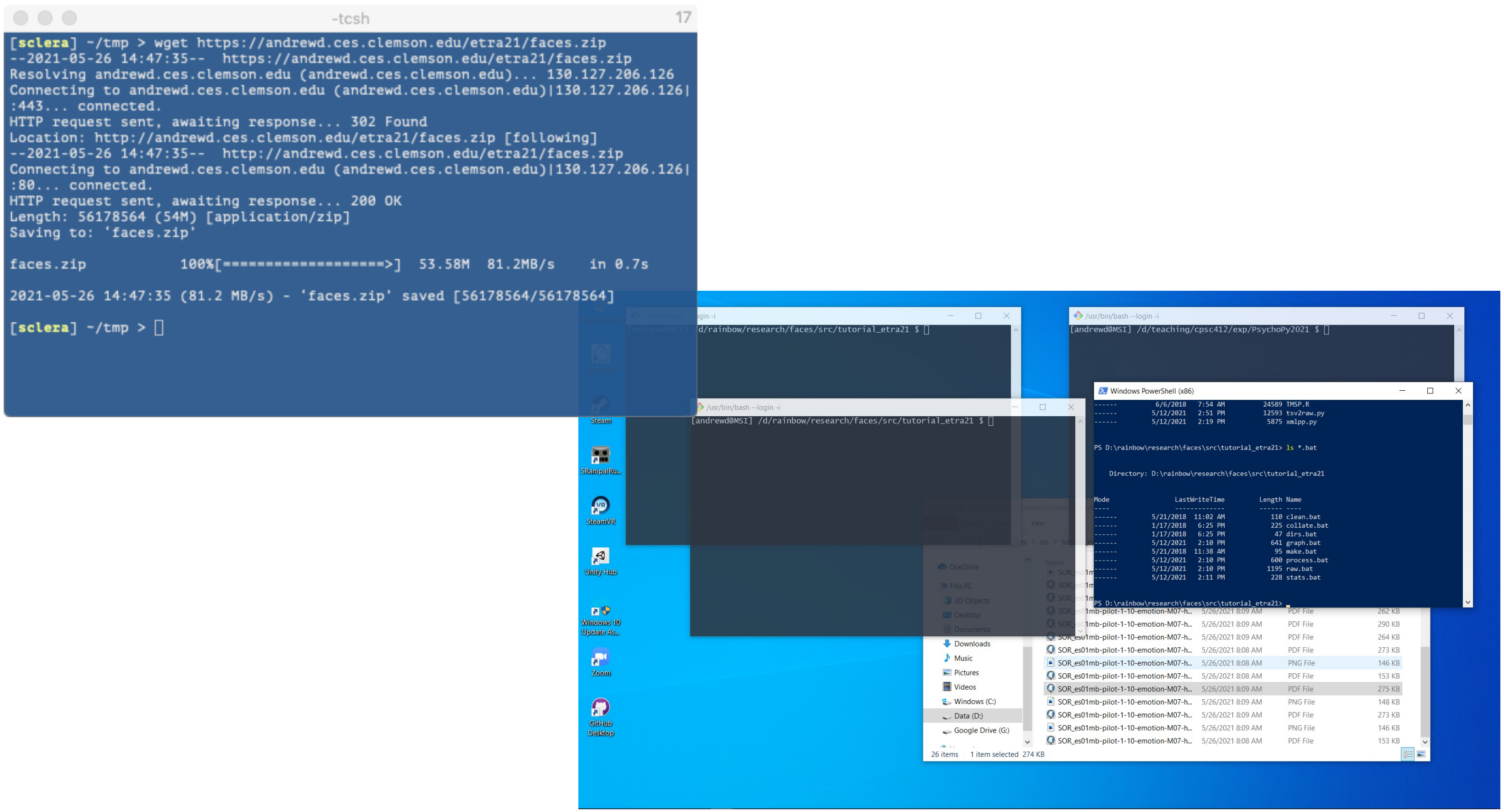
Areas of interest:

- both eyes

- left eye
- right eye
- nose
- mouth

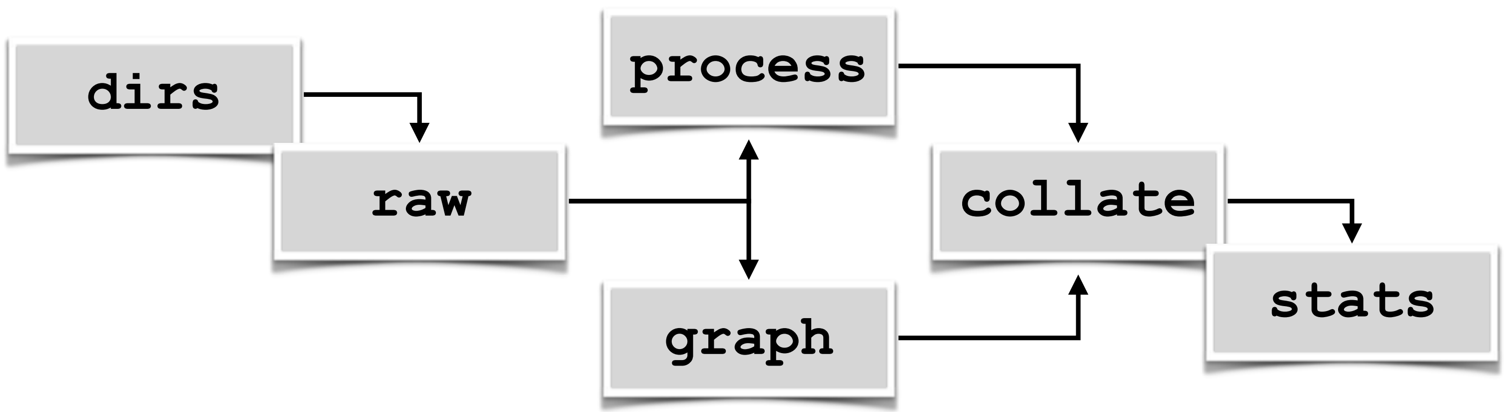
https://andrewd.ces.clemson.edu/cost21/faces.zip

How to run the python scripts...



Gaze analytics pipeline overview

- Main targets (e.g., *nix `Makefile` or Windows `bat` files)
- Idea is to type one command and go for coffee
- Return from coffee and write paper
- 5 easy steps



Gaze analytics pipeline overview

- Main targets (e.g., *nix `Makefile` or Windows `bat` files)
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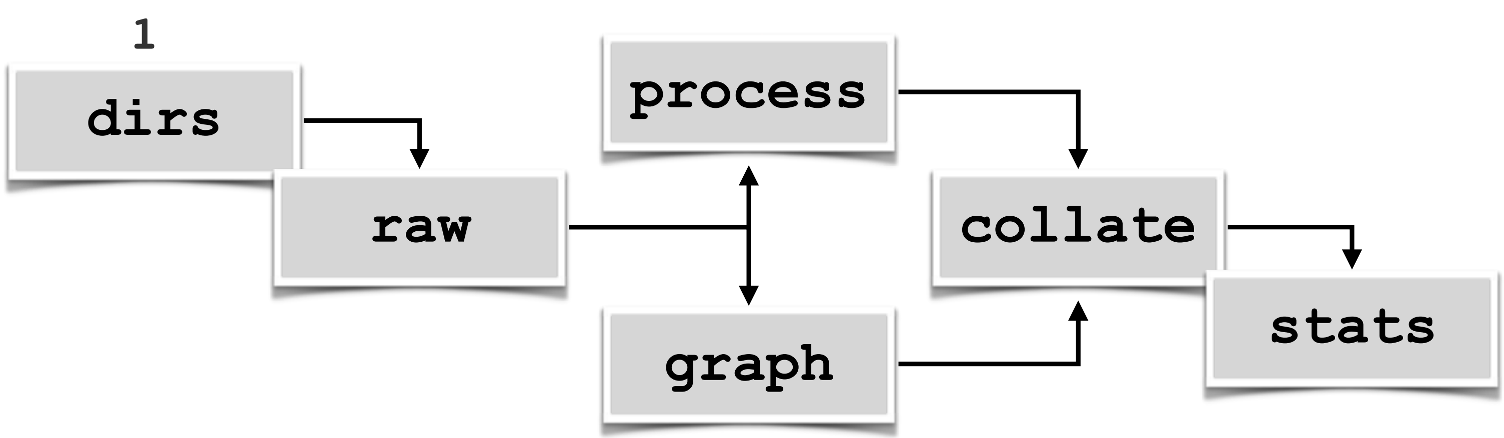
- 5 easy steps

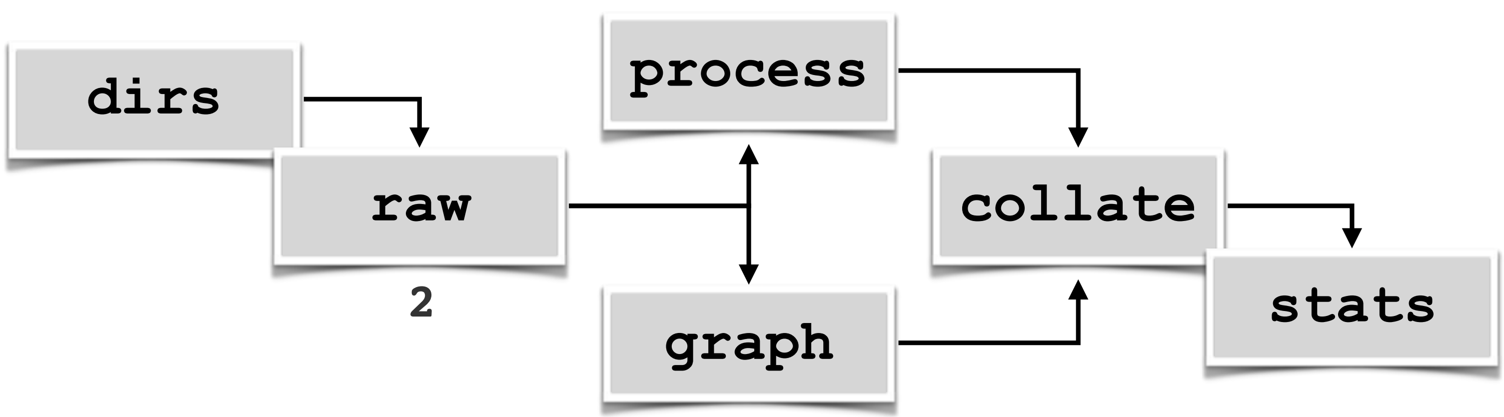
  1. `dirs`



Gaze analytics pipeline overview

- Main targets (e.g., *nix `Makefile` or Windows `bat` files)
- Idea is to type one command and go for coffee
- Return from coffee and write paper
- 5 easy steps:

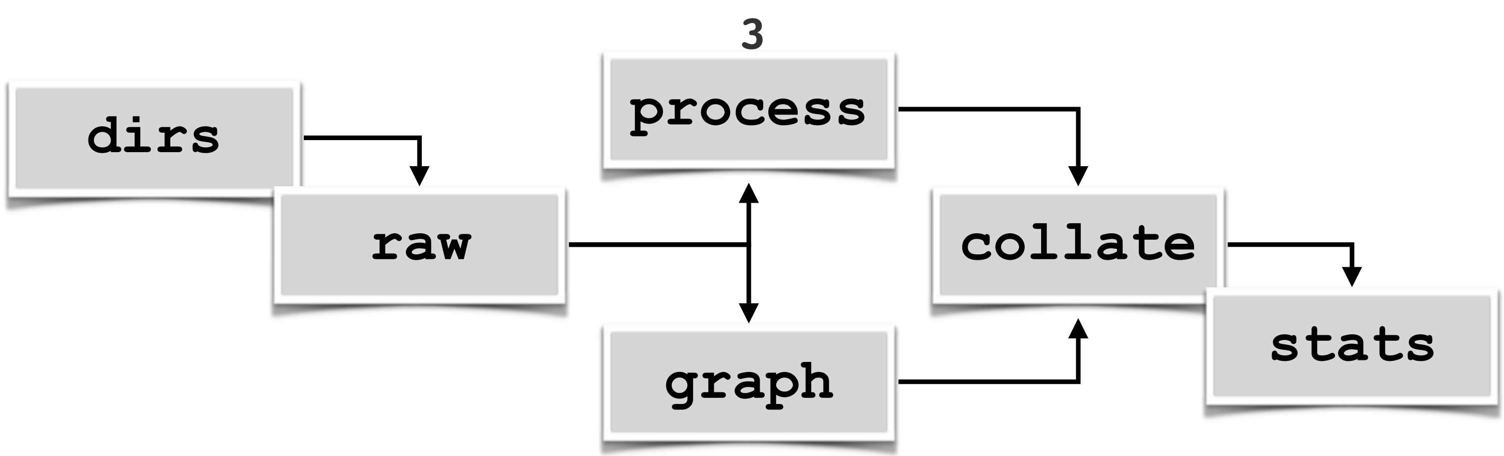
  `1. dirs; 2. raw`



Gaze analytics pipeline overview

- Main targets (e.g., *nix `Makefile` or Windows `bat` files)
- Idea is to type one command and go for coffee
- Return from coffee and write paper
- 5 easy steps:

  `1. dirs; 2. raw; 3. process`



Gaze analytics pipeline overview

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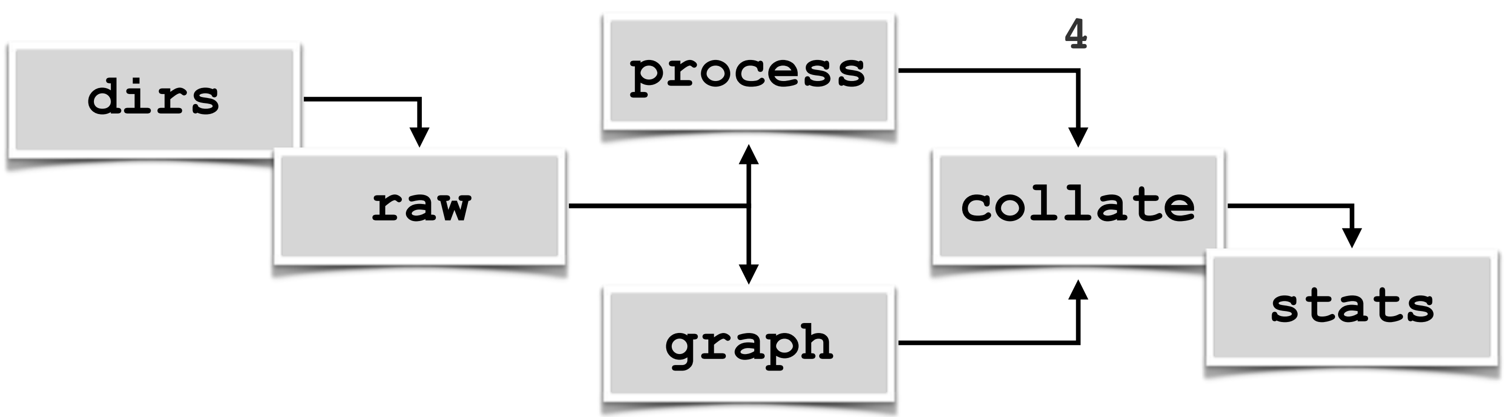
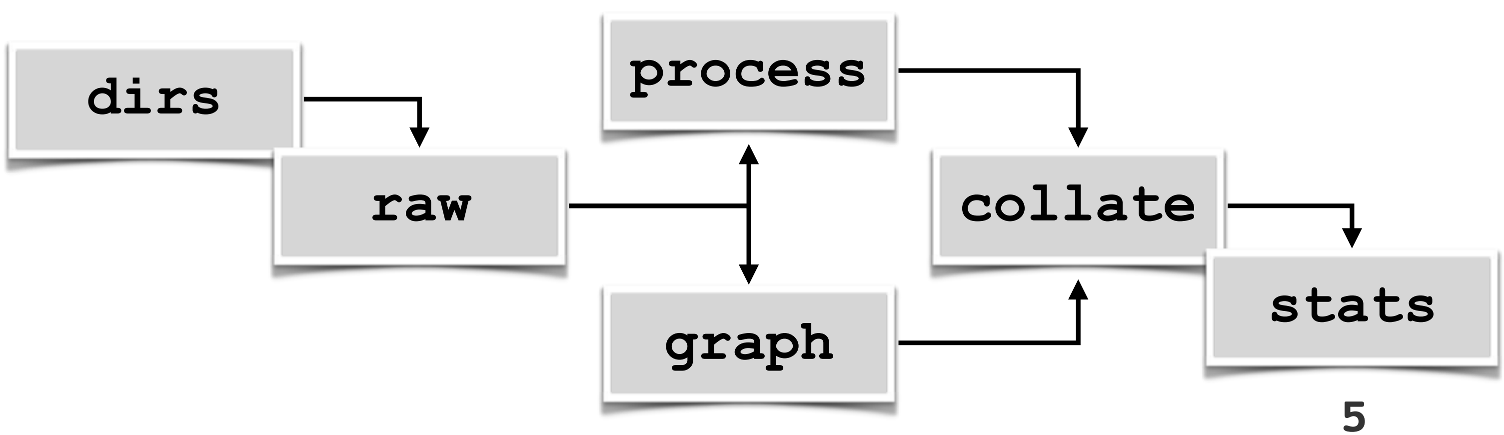
  `1. dirs; 2. raw; 3. process; 4. collate`



Gaze analytics pipeline overview

- Main targets (e.g., *nix `Makefile` or Windows `bat` files)
- Idea is to type one command and go for coffee
- Return from coffee and write paper
- 5 easy steps:

  `1. dirs; 2. raw; 3. process; 4. collate; 5. stats`



Gaze analytics pipeline overview

The python and R scripts:

1. `mkdir`	set up directory (basic OS command)
2. `tsv2raw.py`	parse vendor data into `.raw` data
3. `filter.py`	process `.raw` data (event detection)
`graph.py`	visualize data
4. `collate-*.py`	collate to `.csv` data
5. `*.R`	do the stats

Linux or macOS:	use `Makefile`
Windows:	use `.bat` files

Gaze analytics pipeline overview

Windows (using `.bat` files):

1. `.\dirs.bat`	set up directory (basic OS command)
2. `.\raw.bat`	parse vendor data into `.raw` data
3. `.\process.bat`	process `.raw` data (event detection)
`.\graph.bat`	visualize data
4. `.\collate.bat`	collate to `.csv` data
5. `.\stats.bat`	do the stats

Windows: or use `.\make.bat` file

Gaze analytics pipeline overview

Linux or macOS (using `Makefile`):

1. `make dirs`	set up directory
2. `make raw`	parse vendor data into `.raw` data
3. `make process`	process `.raw` data (event detection)
`make graph`	visualize data
4. `make collate`	collate to `.csv` data
5. `make stats`	do the stats

Linux or macOS: or simply use `make`

Gaze analytics pipeline: essential information

- All of this information is used by scripts:
  - screen resolution: `1024 x 768`
  - screen dimensions (diagonal): `19 in`
  - sampling rate: `500 Hz`
  - viewing distance: `23.62 in (60 cm)`
  - AOIs: `software (Scribus)`

- Also need directories:
  - `indir`: `../../data/tutorial_etra18/`
  - `imgdir`: `../../stimulus/static/screenshots`
  - `pltdir`: `./plots/`
  - `outdir`: `./data`
  - `rawdir`: `./data/raw`

Gaze analytics pipeline: objectives

- Process raw gaze data into fixations, fixation count, etc.

visual angle conversion
• width, height of screen (e.g., 1024 x 768) • screen dimensions (diagonal, e.g., 19 inches) • viewing distance (e.g., 23.62 inches)

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Butterworth smoothing
• filter order (e.g., 2nd, 4th, etc.) • sampling rate (e.g., 60 Hz) • cutoff frequency (e.g., 6.15 Hz)

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- Process raw gaze data into fixations, fixation count, etc.

```
visual angle conversion
• width, height of screen (e.g., 1024 x 768)
• screen dimensions (diagonal, e.g., 19 inches)
• viewing distance (e.g., 23.62 inches)
```

```
Butterworth smoothing
• filter order (e.g., 2nd, 4th, etc.)
• sampling rate (e.g., 60 Hz)
• cutoff frequency (e.g., 6.15 Hz)
```

```
Savitzky-Golay differentiation
• filter width (e.g., 3)
• degree (e.g., 3, 3rd order)
• order (e.g., 1 for differentiation, 0 for smoothing)
```

Gaze analytics pipeline: objectives

- Process raw gaze data into fixations, fixation count, etc.

visual angle conversion

- width, height of screen (e.g., 1024 x 768)
- screen dimensions (diagonal, e.g., 19 inches)
- viewing distance (e.g., 23.62 inches)

~~**Butterworth smoothing**~~

- ~~filter order (e.g., 2nd, 4th, etc.)~~
- ~~sampling rate (e.g., 60 Hz)~~
- ~~cutoff frequency (e.g., 6.15 Hz)~~

Savitzky-Golay differentiation

- filter width (e.g., 3)
- degree (e.g., 3, 3rd order)
- order (e.g., 1 for differentiation, 0 for smoothing)

thresholding

- velocity (e.g., 36 deg/s)

Critical notes on scripts

- None of the scripts are ready “out of the box”
- None of the scripts can easily be ported to other projects

- Why? Not possible to predict future study design

- What needs to be adapted?
  - file name composition, e.g.,

```
SOR_stud10-pilot-2-9-emotion-M04-sad.raw
```

  - file name encodes:

```
subj-group-block-trial-task-stim-type
```

Gaze analytics pipeline: vendor data

- Vendor data comes in various formats, usually plain text

```
RECORDING_SESSION_LABEL Group_VP        blocknr trialnr task
emotion gender  face    dc_x    list    TIMESTAMP
LEFT_GAZE_X     LEFT_GAZE_Y     LEFT_PUPIL_SIZE RIGHT_GAZE_X
RIGHT_GAZE_Y    RIGHT_PUPIL_SIZE        RESPONSE
IS_CORRECT
es01mb  stud    1       1       emotion surprised       male
M08     80      1       2154988,00      78,10   463,20  1296,00
126,00  467,40  1205,00 surprised       Correct
es01mb  stud    1       1       emotion surprised       male
M08     80      1       2154990,00      77,80   464,10  1299,00
126,30  467,20  1204,00 surprised       Correct
es01mb  stud    1       1       emotion surprised       male
M08     80      1       2154992,00      79,30   464,50  1296,00
125,50  467,00  1202,00 surprised       Correct
es01mb  stud    1       1       emotion surprised       male
M08     80      1       2154994,00      80,50   464,50  1294,00
125,00  467,00  1201,00 surprised       Correct
…
```

Gaze analytics pipeline: parse vendor data

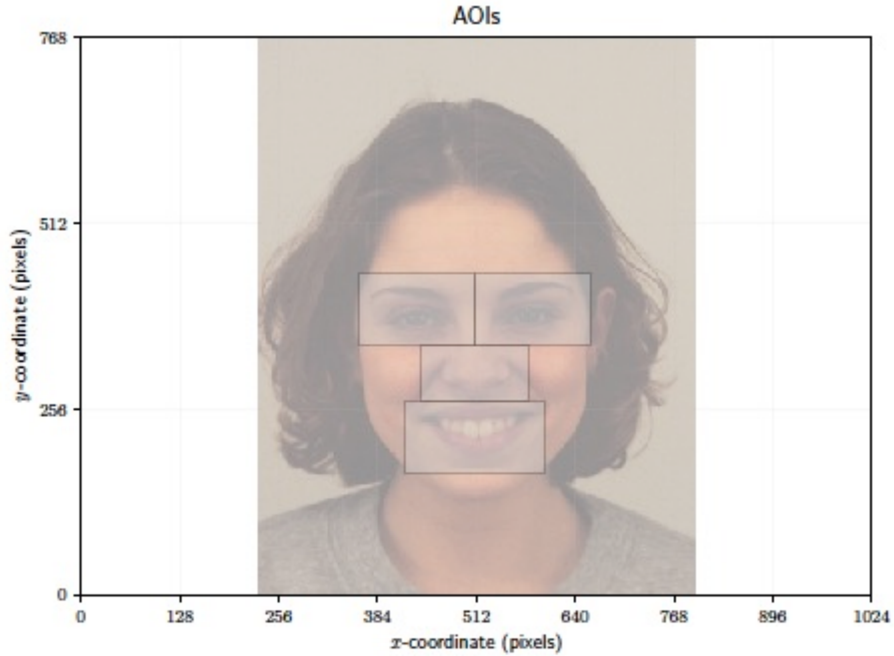
- Just want to extract raw (unprocessed) data: (x, y, t)

```
0.079785 0.613216 61.449674 2235252.000000
0.079443 0.612891 61.602661 2235254.000000
0.079785 0.612630 61.602661 2235256.000000
0.079980 0.613411 61.398678 2235258.000000
0.080029 0.613802 61.398678 2235260.000000
0.080029 0.613997 61.398678 2235262.000000
0.079736 0.613932 61.398678 2235264.000000
0.079443 0.613411 61.398678 2235266.000000
0.079541 0.613086 61.449674 2235268.000000
0.079541 0.612956 61.347683 2235270.000000
0.079395 0.612760 61.245692 2235272.000000
0.079297 0.612630 61.398678 2235274.000000
0.079932 0.612370 61.602661 2235276.000000
0.080127 0.612500 61.500669 2235278.000000
0.079541 0.612891 61.500669 2235280.000000
0.079541 0.612760 61.551665 2235282.000000
0.079590 0.613411 61.551665 2235284.000000
...
```

Gaze analytics pipeline: graph

- Check stimulus image and AOI position
- Important to verify coordinates

`*-aois.pdf`

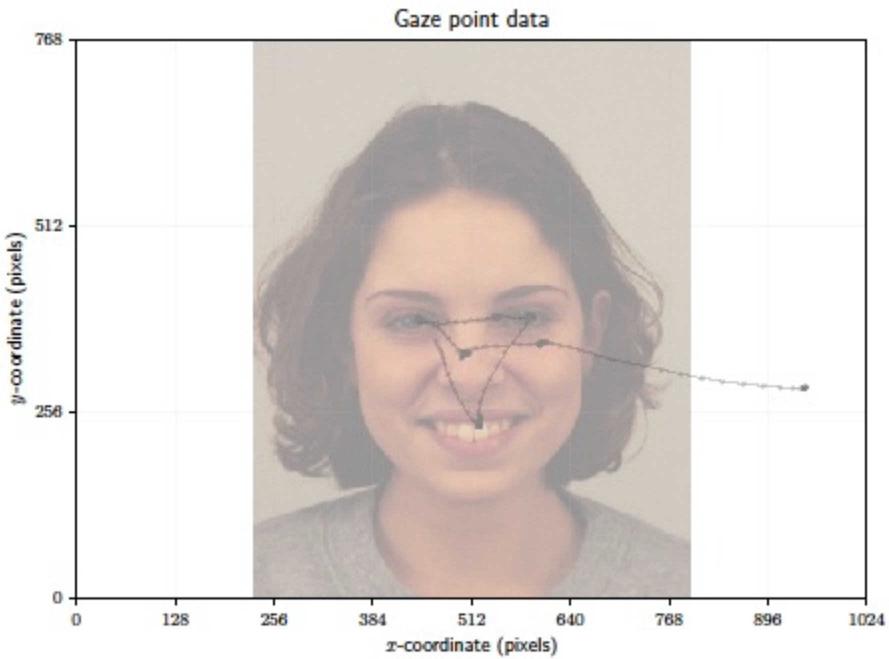


Gaze analytics pipeline: graph

- Check raw data (2D)

$$g_i = (x_i, y_i, t_i)$$

`*-gzpt.pdf`



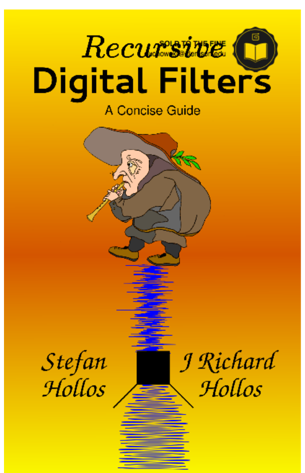
Gaze analytics pipeline: graph

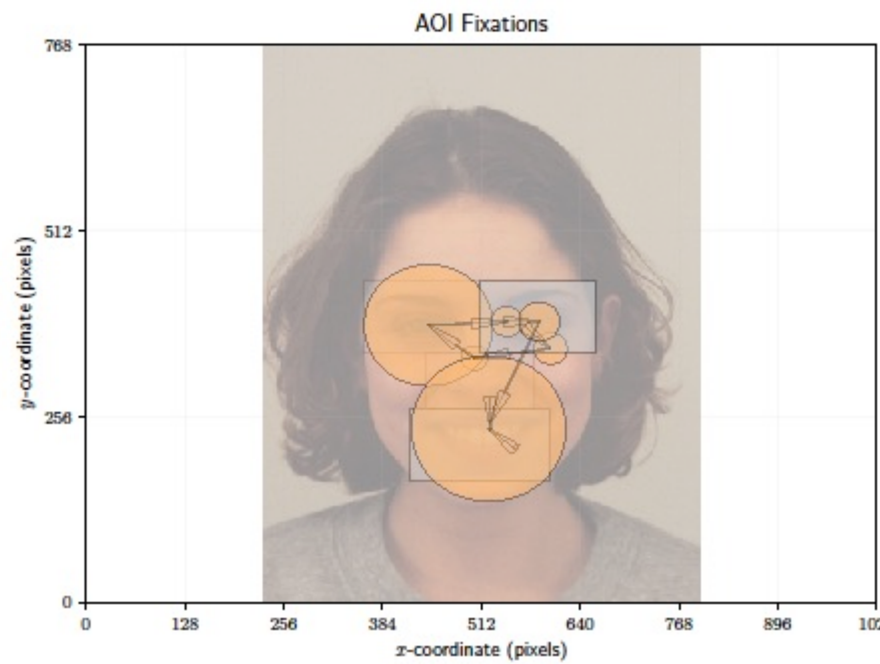
- Check fixations in AOIs

$$\dot{x}_n^s(t) = 1/(\Delta t^s)\left(\sum_{i=-p}^{p} h_i^{t,s} x_{n-i} - \sum_{i=-q}^{q} g_i^{t,s} \dot{x}_{n-i}\right)$$

`*-fxtn-aoi.pdf`

  - Savitzy-Golay filter





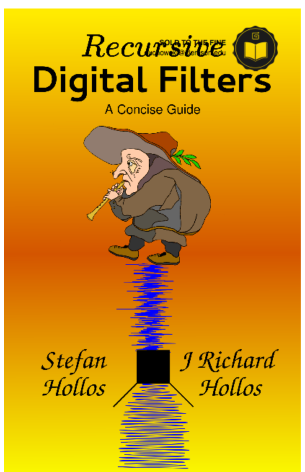
Gaze analytics pipeline: graph

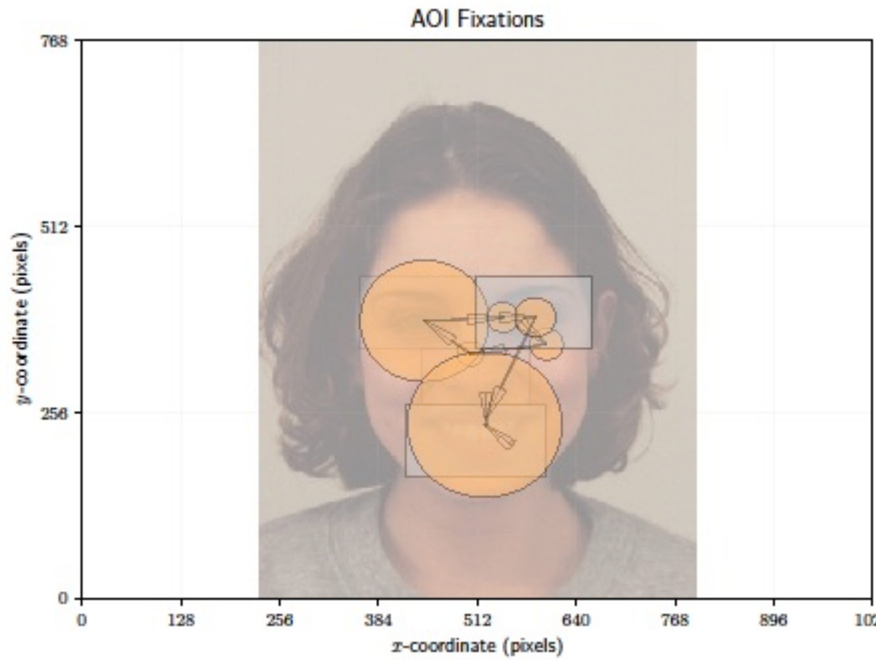
- Check fixations in AOIs

$$\dot{x}_n^s(t) = 1/(\Delta t^s)\left(\sum_{i=-p}^{p} h_i^{t,s} x_{n-i} - \sum_{i=-q}^{q} g_i^{t,s}\dot{x}_{n-i}\right)$$

`*-fxtn-aoi.pdf`

  - Savitzy-Golay filter





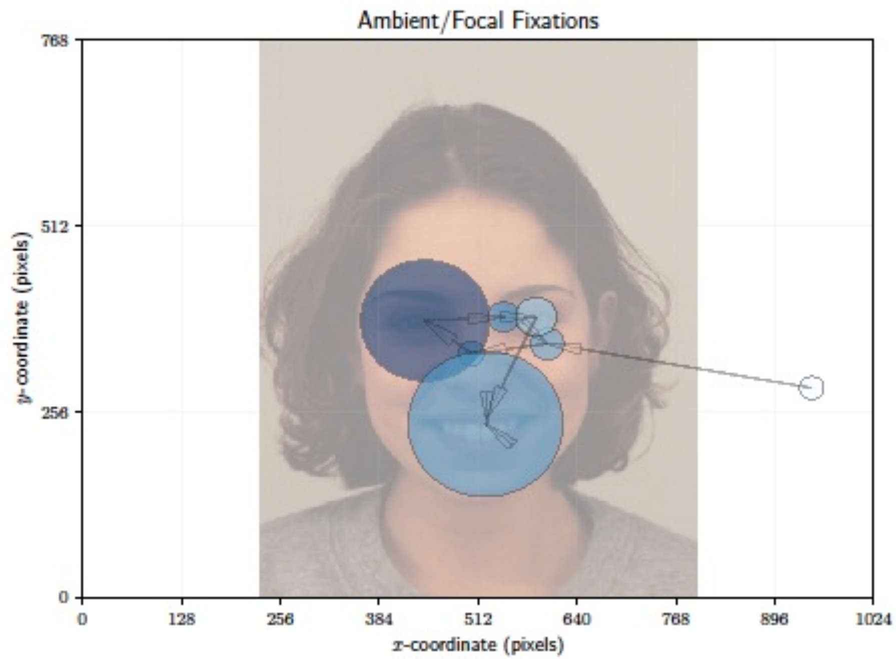
Gaze analytics pipeline: graph

- Check ambient/focal fixations

`*-affx.pdf`

$$\mathcal{K}_i = \frac{d_i - \mu_d}{\sigma_d} - \frac{a_{i+1} - \mu_a}{\sigma_a}$$

- fixation dur. – sacc. ampl.
- z-scores
- $\mathcal{K} > 0$ focal viewing
- $\mathcal{K} < 0$ ambient viewing



Gaze analytics pipeline: graph

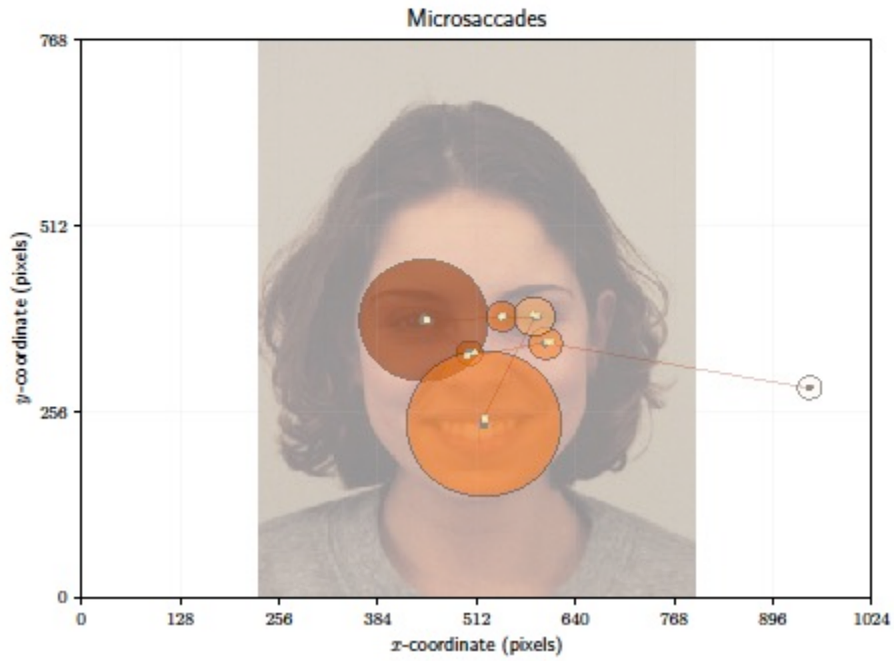
- Check microsaccades within ambient/focal fixations

```
*-ksac.pdf
```

$$\dot{x}_n = \frac{x_{n+2} + x_{n+1} - x_{n-1} - x_{n-2}}{6\Delta t}$$

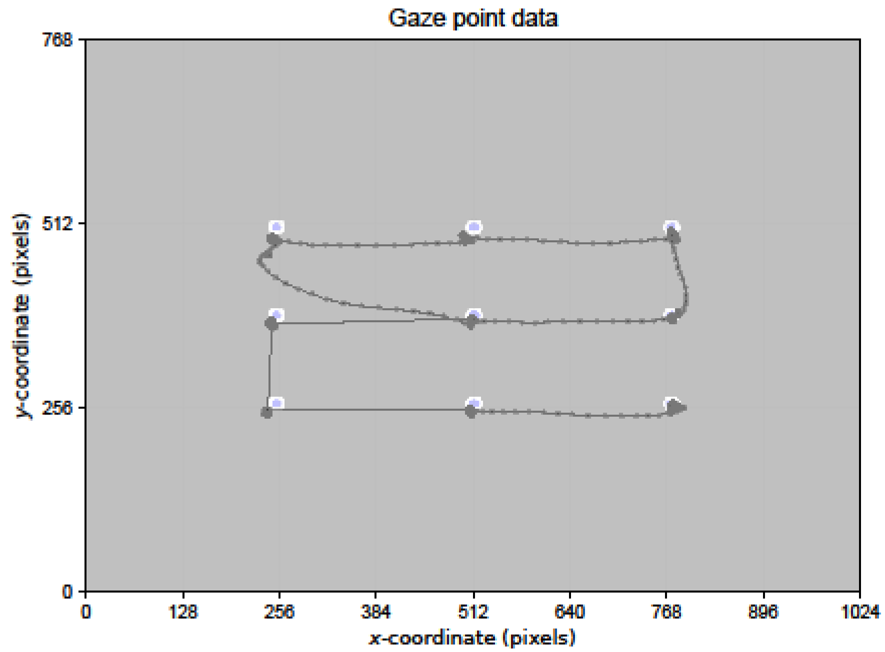
$$\sigma_x = \sqrt{\langle \dot{x}^2 \rangle - \langle \dot{x} \rangle^2}, \quad \sigma_y = \sqrt{\langle \dot{y}^2 \rangle - \langle \dot{y} \rangle^2}$$

$$\eta_x = \lambda \sigma_x, \quad \eta_y = \lambda \sigma_y$$



Gaze analytics pipeline: graph

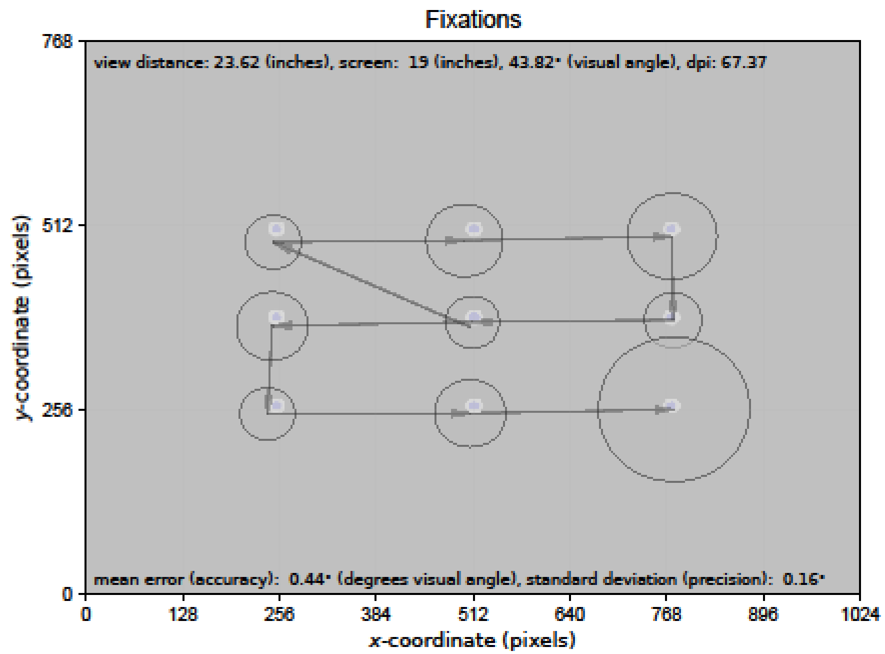
- Can do this over grid / calibration image (validation)
- Did you remember to include this in the stimuli?



Gaze analytics pipeline: graph

- This really helps in fine-tuning event detection filters
- Can also compute your own accuracy & precision
  - really useful for reporting

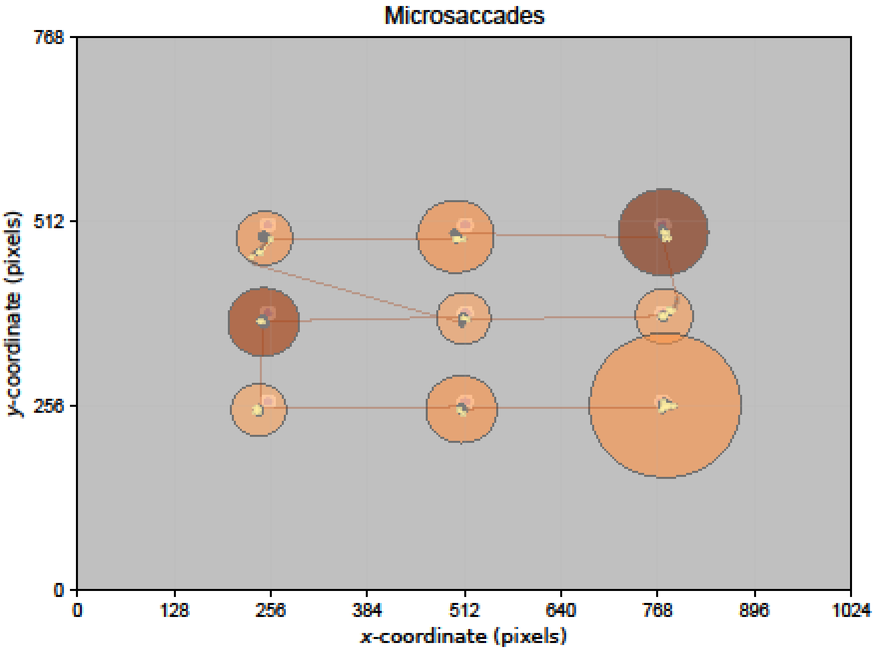
$$A = \sum_{i=1}^{M} \left(\frac{\sum_{j=1}^{N} \frac{\|T_i - P_{i,j}\|}{N}}{M} \right)$$



  - algorithm:
    - for each of N fixation points $P_{i,j}$
      - using kd-tree, find closest M calibration points T_i
      - compute distance $\|T_i - P_{i,j}\|$

Gaze analytics pipeline: graph

- Look at microsaccades in ambient/focal fixations again
- Cause they're cool



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Gaze analytics pipeline: process

- Once happy with visualizations, process data
- Will end up with various `*.dat` files, one per subject:

1. `*-pdwt.dat` wavelet transform (nothing to see here)
2. `*-pICA.dat` Index of Pupillary Activity (IPA)
3. `*-pups.dat` pupil diameter data (tricky)
4. `*-smth.dat` smoothed (Butterworth) data
5. `*-fxtn.dat` fixations
6. `*-sacc.dat` saccades
7. `*-msac.dat` microsaccades
8. `*-msrt.dat` microsaccade rate
9. `*-amfo.dat` ambient/focal K coefficient
10. `*-fxtn-aois.dat` fixations in AOIs

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Gaze analytics pipeline: collate

- Now collate data to prepare for stats processing
- Will end up with various `*.csv` files, one per metric:

1. ~~`pdwt.csv`~~	wavelet transform (wouldn't make sense)
2. `pICA.csv`	Index of Pupillary Activity (IPA)
3. ~~`pups.csv`~~	pupil diameter (can get this, need baseline)
4. ~~`smth.csv`~~	smoothed (Butterworth) data
5. `fxtn.csv`	fixations
6. `sacc.csv`	saccades
7. `msac.csv`	microsaccades
8. `msrt.csv`	microsaccade rate
9. `amfo.csv`	ambient/focal K coefficient
10. `fxtn-aois.csv`	fixations in AOIs

Gaze analytics pipeline: analyze

- Traditional metrics
  - fixations
  - fixation durations

- Novel / advanced metrics
  - **ambient / focal fixations**
  - Index of Pupillary Activity
  - Low/High Index of Pupillary Activity
  - microsaccade amplitude, rate

Discerning Ambient/Focal Attention with Coefficient $\mathcal{K}$

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ANDREW DUCHOWSKI, Clemson University, Clemson, SC, USA
IZABELA KREJTZ, University of Social Sciences and Humanities, Warsaw, Poland
AGNIESZKA SZARKOWSKA, University of Warsaw, Warsaw, Poland
AGATA KOPACZ, National Information Processing Institute, Warsaw, Poland

We introduce coefficient $\mathcal{K}$, defined on a novel parametric scale, derived from processing a traditionally eye-tracked time course of eye movements. Positive and negative ordinates of $\mathcal{K}$ indicate *focal* or *ambient* viewing, respectively, while the abscissa serves to indicate time, so that $\mathcal{K}$ acts as a dynamic indicator of fluctuation between ambient/focal visual behavior. The coefficient indicates the difference between fixation duration and its subsequent saccade amplitude expressed in standard deviation units, facilitating parametric statistical testing. To validate $\mathcal{K}$ empirically, we test its utility by capturing ambient and focal attention during serial and parallel visual search tasks (Study 1). We then show how $\mathcal{K}$ quantitatively depicts the difference in scanning behaviors when attention is guided by audio description during perception of art (Study 2).

Categories and Subject Descriptors: J.4 [**Computer Applications**]: Social and Behavioural Sciences—*Psychology.*

General Terms: Human Factors

Additional Key Words and Phrases: ambient-focal attention, visual attention dynamics, serial vs. parallel search

1. INTRODUCTION

There is an increasing demand for characterization of viewer behavior through analysis of eye movements. Efforts are underway to surpass traditional categorization of the captured eye gaze sequence (x_i, y_i, t_i) as fixations and saccades into higher-level descriptors of visual behavior. For example, Bednarik et al. [2012] explored eye movement features that could best describe the differences in gaze behavior during intentional and non-intentional interaction, e.g., deciding if the user is about to issue a command. They used a Support Vector Machine (SVM) approach to differentiate pupil diameter from a baseline recording for this purpose. Bulling et al. [2013] attempted to classify continuous electro-oculography (EOG) signals into a vector of binary descriptors of everyday life situations, i.e., whether or not the user is interacting socially, concentrating on a mental task, engaging in a physical activ-

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Gaze analytics pipeline: analyze

- Traditional metrics
  - fixations
  - fixation durations

- Novel / advanced metrics
  - ambient / focal fixations
  - **Index of Pupillary Activity**
  - Low/High Index of Pupillary Activity
  - microsaccade amplitude, rate

The Index of Pupillary Activity

Measuring Cognitive Load *vis-à-vis* Task Difficulty with Pupil Oscillation

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ABSTRACT

A novel eye-tracked measure of the frequency of pupil diameter oscillation is proposed for capturing what is thought to be an indicator of cognitive load. The proposed metric, termed the Index of Pupillary Activity, is shown to discriminate task difficulty *vis-à-vis* cognitive load (if the implied causality can be assumed) in an experiment where participants performed easy and difficult mental arithmetic tasks while fixating a central target (a requirement for replication of prior work). The paper's contribution is twofold: full documentation is provided for the calculation of the proposed measurement which can be considered as an alternative to the existing proprietary Index of Cognitive Activity (ICA). Thus, it is possible for researchers to replicate the experiment and build their own software which implements this measurement. Second, several aspects of the ICA are approached in a more data-sensitive way with the goal of improving the measurement's performance.

Author Keywords

pupillometry; eye tracking; task difficulty

ACM Classification Keywords

H.1 Models and Principles: User/Machine Systems; J.4 Computer Applications: Social and Behavioral Sciences

INTRODUCTION

Systems that can detect and respond to their users' cognitive load have the potential to improve both users' experiences and outcomes in many domains: students and teachers, drivers, pilots, and surgeons may all benefit from systems that can detect when their jobs are too hard or easy and dynamically adapt the difficulty [3, 20, 41, 71, 11]. Key to this functionality is the ability to accurately estimate a person's cognitive load without distracting them from their tasks.

Estimation of human workload is couched in Cognitive Load Theory (CLT) [65]. Because CLT aims to model cognitive aspects of human behavior, it is relevant to several Human-Computer Interaction (HCI) research areas, including human-centered design, human cognition modeling, usability, and learning systems (e.g., e-learning) [48, 24]. Estimating the user's workload is helpful for many situations where people interact with computing devices or machines [20]. Minimizing cognitive load is suggested as an integral part of human-centered design [10]. Pfleging et al. [53] and Palinko and Kun [50] provide notable examples related to HCI, including automotive and online learning domains. Bailey and Iqbal [3] show how moment-to-moment detection of mental workload can help reduce the interruption cost of notifications when performing interactive tasks such as driving. Other important applications include surgery [28, 29] and flight safety [52].

Cognitive Load Theory can play an important role in the design of interactive systems as it can guide designers of such systems to avoid overloading users. For example, Yuksel et al. [71] devised an interactive music learning interface that adapts to the user's level of cognitive load as measured by functional near-infrared spectroscopy (fNIRS). They note, however, that reliable measurement of cognitive load is the weak link between CLT and HCI. Other physiological measures include heart rate variability (HRV), electrodermal activity (EDA, previously galvanic skin response (GSR)), photoplethysmogram-based stress induced vascular index (sVRI), and blink rate [9]. With the exception of blink rate, all of these methods are invasive, relying on physical contact with the user. A non-invasive, reliable measure of cognitive load is thus highly desirable.

Of the three predominant cognitive load measurement methods in CLT studies, namely self-reporting, the dual-task paradigm, and physiological measures [71], eye tracking, of the latter type, offers the greatest potential for delivering a non-invasive estimate of cognitive load (for an excellent recent review of psychophysiological measures with a focus on HCI, see Cowley et al. [11]). Measurement of gaze for estimating cognitive

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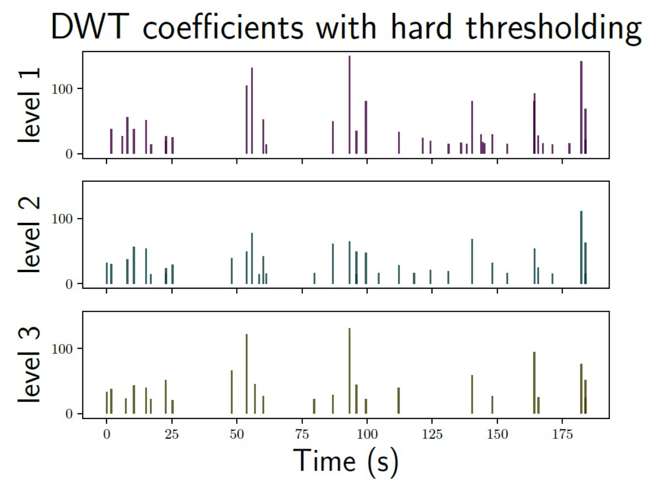
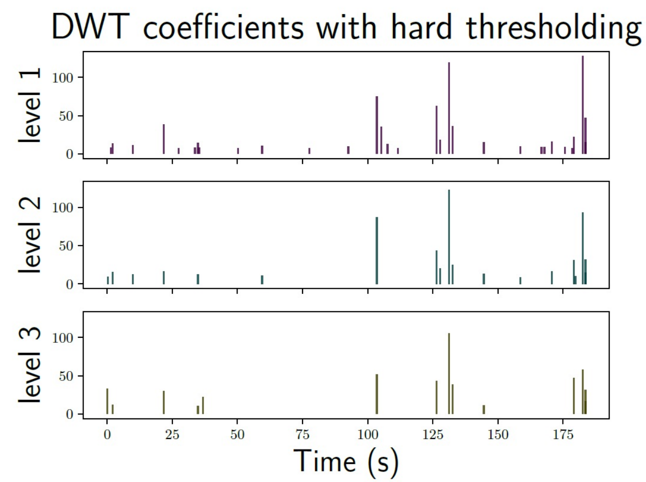
1

Gaze analytics pipeline: analyze

- Traditional metrics
  - fixations
  - fixation durations

- Novel / advanced metrics
  - ambient / focal fixations
  - **Index of Pupillary Activity**
  - Low/High Index of Pupillary Activity
  - microsaccade amplitude, rate





Gaze analytics pipeline: analyze

- Traditional metrics
  - fixations
  - fixation durations

- Novel / advanced metrics
  - ambient / focal fixations
  - Index of Pupillary Activity
  - **Low/High Index of Pupillary Activity**
  - microsaccade amplitude, rate

The Low/High Index of Pupillary Activity

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ABSTRACT

A novel eye-tracked measure of pupil diameter oscillation is derived as an indicator of cognitive load. The new metric, termed the Low/High Index of Pupillary Activity (LHIPA), is able to discriminate cognitive load (*vis-à-vis* task difficulty) in several experiments where the Index of Pupillary Activity fails to do so. Rationale for the LHIPA is tied to the functioning of the human autonomic nervous system yielding a hybrid measure based on the ratio of Low/High frequencies of pupil oscillation. The paper's contribution is twofold. First, full documentation is provided for the calculation of the LHIPA. As with the IPA, it is possible for researchers to apply this metric to their own experiments where a measure of cognitive load is of interest. Second, robustness of the LHIPA is shown in analysis of three experiments, a restrictive fixed-gaze number counting task, a less restrictive fixed-gaze n-back task, and an applied eye-typing task.

Author Keywords

pupillometry; eye tracking; task difficulty

CCS Concepts

•**Human-centered computing → Human computer interaction (HCI);** User studies

INTRODUCTION & BACKGROUND

Recent interest in the measurement of cognitive load has emerged from a variety of applied human factors settings, e.g., the automobile, flightdeck, operating room, and the classroom, to name a few [47, 5, 26, 22, 48, 29, 43, 59]. As noted by Fridman et al. [19], the breadth and depth of the published work highlights the difficulty of identifying useful measures of cognitive load that do not interfere with or influence behavior. Moreover, if the measure is based on pupil diameter, as a good deal of these metrics are, then it is also important to show that the metric is not susceptible to effects of luminance or off-axis distortion of the apparent pupil (e.g., as captured by the typically stationary camera) [15].

As introduced by Sweller [57, 58], cognitive load is a theoretical construct describing the internal processing of tasks that cannot be observed directly [41]. One of the most popular measures to assume indication of cognitive load is pupil diameter, originating with Hess and Polt [25] and later bolstered by Peavler [49], who showed correlation between pupil dilation and problem difficulty. It is generally considered that pupil diameter provides a "very effective index of the momentary load on a subject as they perform a mental task" [34].

Early studies of task-evoked pupillary response to cognitive load used specialized pupillometers to measure pupil diameter [1, 8, 7]. Because of their improved accuracy and reduced cost, eye trackers have become popular for the estimation of cognitive load via measurement of pupil diameter, which most eye trackers report as a matter of course [54, 11, 53]. The general approach to cognitive load estimation with eye-tracked pupil diameter relies on measurement relative to a baseline. Numerous examples of eye-tracked baseline-related pupil diameter measurements exist, focusing either on inter- [27, 38, 41, 36], or intra-trial baseline differences [54, 39, 30].

Besides pupil diameter, some eye-tracking users infer cognitive load from blink rate [12], while others consider blinks something of an eye-tracking by-product. When blinks occur, the eye tracker loses sight of the pupil, and often outputs some undefined value for gaze position. Other approaches to cognitive load measurement evaluate positional eye movements, including number of fixations [28], fixation durations [18, 32], and number of regressions [4], although these metrics could be considered indirect indicators of cognitive load. More recent approaches to cognitive load measurement use microsaccades (the component of miniature eye movements, along with tremor and drift, made during visual fixation [17]). For a review of the observed relationship between microsaccades and task difficulty, see Duchowski et al. [16]. For a detailed review of Cognitive Load Theory (CLT) and related measures, see Kelleher and Hnin [35], Duchowski et al. [15], and Cowley et al. [14].

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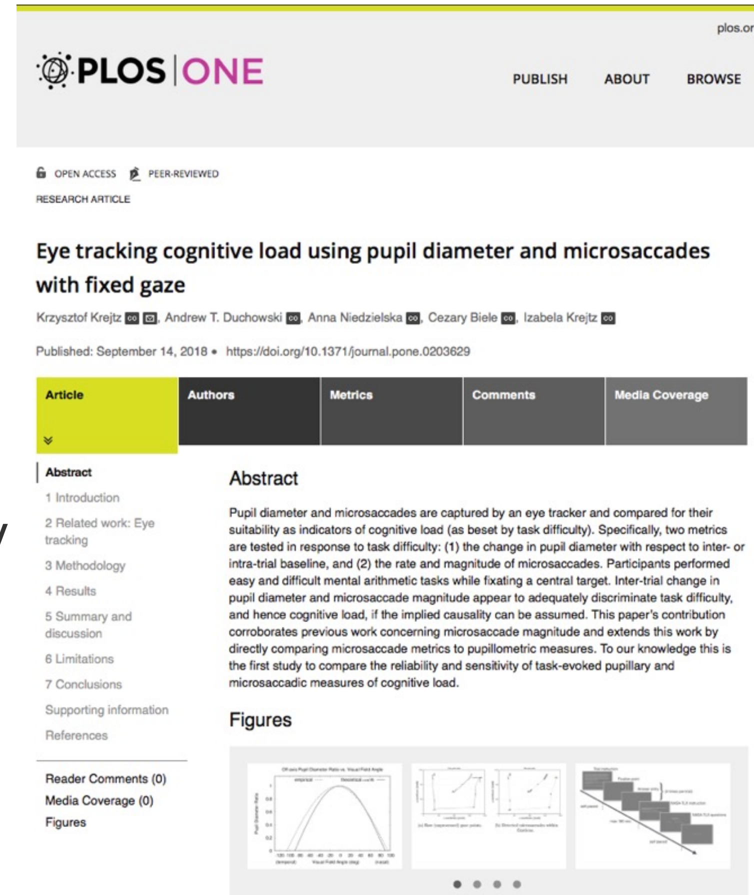
DOI: http://dx.doi.org/10.1145/3313831.3376394

Gaze analytics pipeline: analyze

- Traditional metrics
  - fixations
  - fixation durations

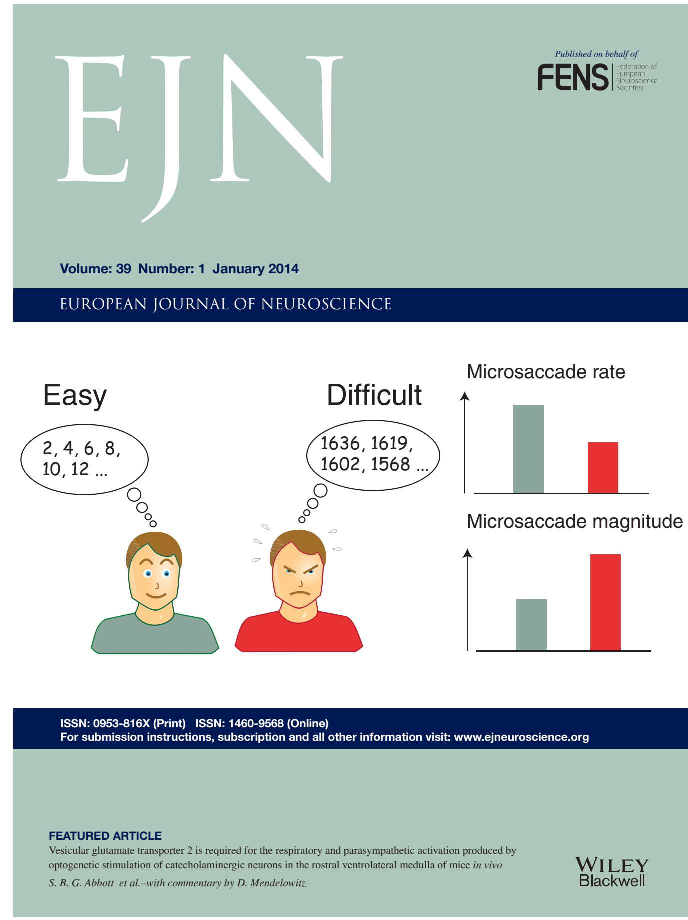
- Novel / advanced metrics
  - ambient / focal fixations
  - Index of Pupillary Activity
  - Low/High Index of Pupillary Activity
  - **microsaccade amplitude, rate**



Gaze analytics pipeline: analyze

- Traditional metrics
  - fixations
  - fixation durations

- Novel / advanced metrics
  - ambient / focal fixations
  - Index of Pupillary Activity
  - Low/High Index of Pupillary Activity
  - **microsaccade amplitude, rate**



Gaze analytics pipeline: analyze

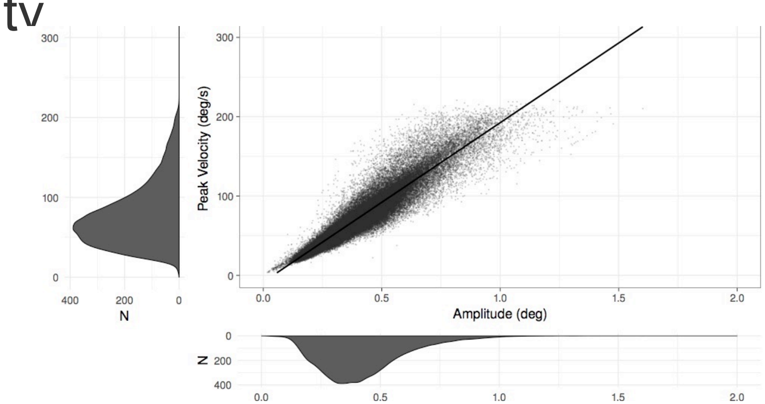
- Traditional metrics
  - fixations
  - fixation durations

$$\dot{x}_n = \frac{x_{n+2} + x_{n+1} - x_{n-1} - x_{n-2}}{6\Delta t}$$

- Novel / advanced metrics
  - ambient / focal fixations
  - Index of Pupillary Activity
  - Low/High Index of Pupillary Activity
  - **microsaccade amplitude, rate**

$$\sigma_x = \sqrt{\langle \dot{x}^2 \rangle - \langle \dot{x} \rangle^2}, \quad \sigma_y = \sqrt{\langle \dot{y}^2 \rangle - \langle \dot{y} \rangle^2}$$

$$\eta_x = \lambda \sigma_x, \quad \eta_y = \lambda \sigma_y$$



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Gaze analytics pipeline: analyze

- Traditional metrics
  - fixations
  - fixation durations

- Novel / advanced metrics
  - ambient / focal fixations
  - Index of Pupillary Activity
  - Low/High Index of Pupillary Activity
  - **microsaccade amplitude, rate**

Article

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From Exploration to Fixation: An Integrative View of Yarbus's Vision

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Abstract
Alfred Lukyanovich Yarbus (1914–1986) pioneered the study of stabilized retinal images, miniature eye movements, and the cognitive influences that act on visual scanning. Yarbus's studies of these different topics have remained fundamentally disconnected and independent of each other, however. In this review, we propose that Yarbus's various research lines are instead deeply and intrinsically interconnected, as are the small eye movements produced during visual fixation and the large-scale scanning patterns associated with visual exploration of objects and scenes. Such apparently disparate viewing behaviors may represent the extremes of a single continuum of oculomotor performance that operates across spatial scales when we search the visual world.

Keywords
Yarbus, saccades, microsaccades, fixation, visual search, fixational eye movements

Introduction

Contemporary research on eye movements and vision owes much of its foundation to the work of Alfred Lukyanovich Yarbus (1914–1986; Wade, 2015). Although the details of Yarbus's life have remained largely obscure to English readers until recently (Tatler, Wade, Kwan, Findlay, & Velichkovsky, 2010), his work influenced powerfully the field of eye movement research, especially since the 1967 English translation of his book, *Eye Movements and Vision*, originally published in Russian in 1965 (Yarbus, 1967).

Yarbus's work on stabilized retinal images (Figure 1) and on the cognitive influences on scanning patterns (Figures 2 and 3) have each had a very strong impact on current oculomotor research (Tatler et al., 2010). These two research lines represent viewing conditions that are polar opposites to each other in a number of ways:

(1) Vision in the absence of eye movements versus vision with unrestricted eye movements.

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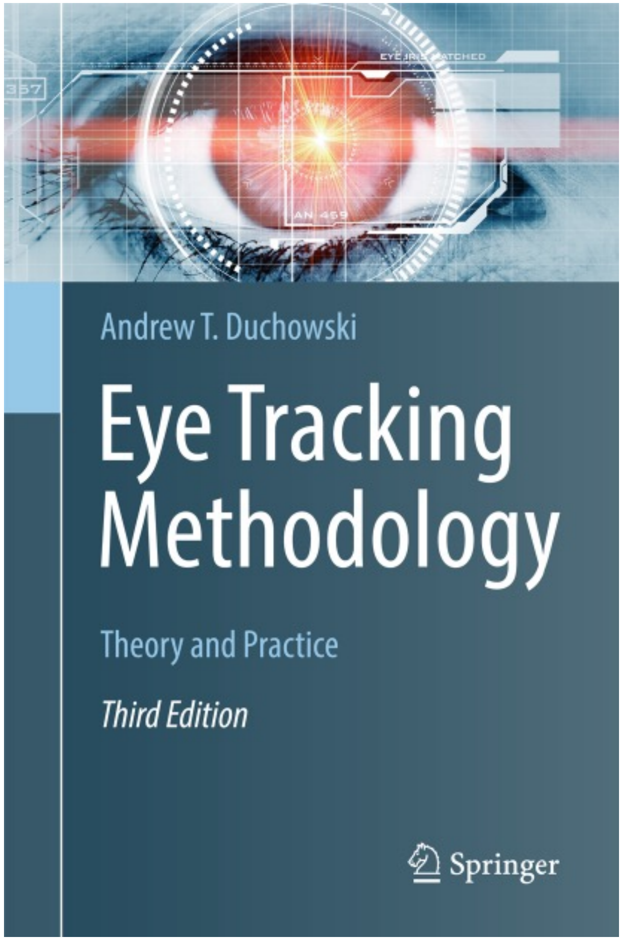
Gaze analytics pipeline: read

- Third edition (2017)

- More details found in the book
  - additional metrics (NNI)
  - microsaccades
  - heatmap visualization
  - binocular eye movement analysis
  - etc.

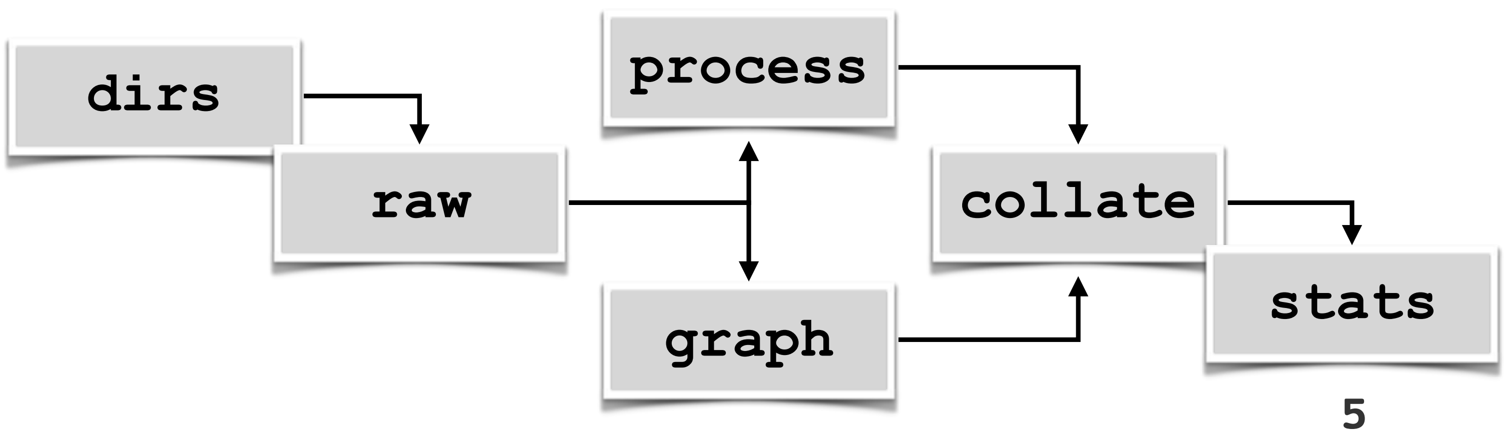


Gaze analytics pipeline: statistics

- Excellent online references for R (maybe dated by now):
  - Baron and Li's Notes on the use of R for psychology experiments and questionnaires:
    - http://www.psych.upenn.edu/~baron/rpsych.html
  - The Personality Project
    - http://www.personality-project.org/r

Gaze analytics pipeline overview

`1. dirs; 2. raw; 3. process; 4. collate; 5. stats`



Windows (using `.bat` files): `.\stats.bat`

Linux or macOS (using `Makefile`): `make stats`

Gaze analytics pipeline:

`*.csv` files, one per metric:

`amfo.csv`	ambient/focal K coefficient
`fxtn.csv`	fixations
`fxtn-aois.csv`	fixations in AOIs
`msac.csv`	microsaccades
`msrt.csv`	microsaccade rate
`pICA.csv`	Index of Pupillary Activity (IPA)
`sacc.csv`	saccades

Gaze analytics pipeline:

One row per fixation:

`amfo.csv`	ambient/focal K coefficient
`fxtn.csv`	fixations
`msrt.csv`	microsaccade rate

One row per fixation in one of the AOIs:

`fxtn-aois.csv`	fixations in AOIs

One row per microsaccade

`msac.csv`	microsaccades

One row per trial (per subject)

`pICA.csv`	Index of Pupillary Activity (IPA)

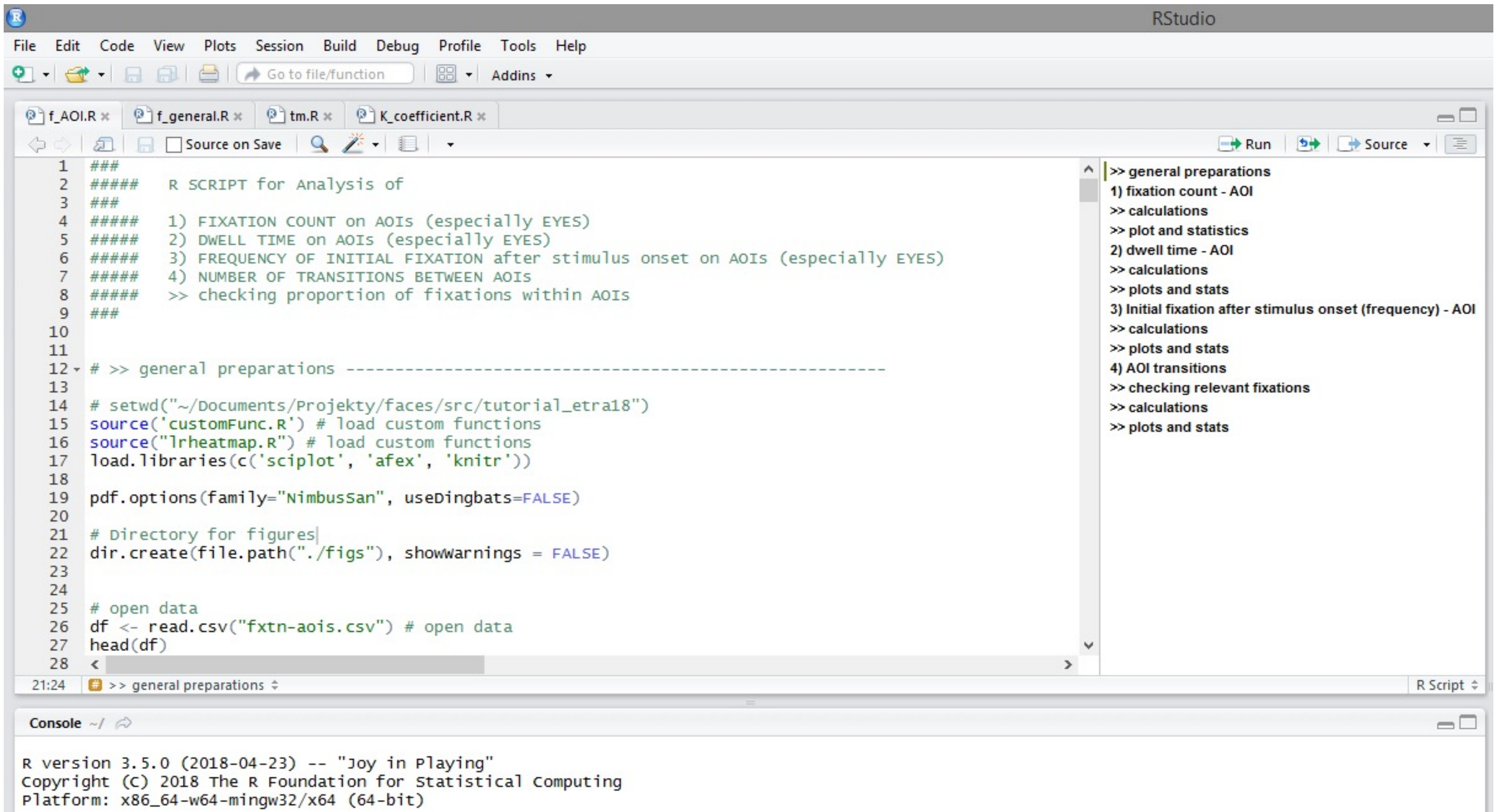
One row per saccade:

`sacc.csv`	saccades

Gaze analytics pipeline: statistics

1. `f_AOI.R` gaze analytics related to AOIs
2. `f_general.R` general measures of scanning behavior
3. `K_coefficient.R` ambient/focal fixations
4. `tm.R` transition matrices and transition entropy

Gaze analytics pipeline: statistics



Gaze analytics pipeline: statistics

1.	`f_AOI.R`	gaze analytics related to AOIs
2.	`f_general.R`	general measures of scanning behavior
3.	`K_coefficient.R`	ambient/focal fixations
4.	`tm.R`	transition matrices and transition entropy

Will end up with various figures in `./figs` and 4 `*.out` files, one per R script:

```
f_AOI.out
f_general.out
K_coefficient.out
tm.out
```

Gaze analytics pipeline: statistics

Code and output/statistics in the `*.out` files:

`f_AOI.out`

```
> ###
> #####   R SCRIPT for Analysis of
> ###
> #####   1) FIXATION COUNT on AOIs (especially EYES)
> #####   2) DWELL TIME on AOIs (especially EYES)
> #####   3) FREQUENCY OF INITIAL FIXATION after stimulus onset on AOIs (esp. EYES)
> #####   4) NUMBER OF TRANSITIONS BETWEEN AOIs
> #####   >> checking proportion of fixations within AOIs
> ###
>
>
> # >> general preparations -------------------------------------------------------
>
>
> …
```

calculated from `fxtn-aois.csv` and `fxtn.csv`

Gaze analytics pipeline: statistics

Code and output/statistics in the `*.out` files:

`f_general.out`

```
> ###
> #####   R SCRIPT for Analysis of
> ###
> #####   1) MICROSACCADES
> #####   >> amplitude
> #####   >> rate = (microsaccade number / total fixation duration)
> #####   .
> #####   2) FIXATIONS
> #####   >> number per trial
> #####   >> duration
> #####   .
> #####   3) PUPIL DILATION
> #####   >> pICA
> ###
> …
```

calculated from `msac.csv`, `msrt.csv` (`and fxtn.csv`), and `pICA.csv`

Gaze analytics pipeline: statistics

Code and output/statistics in the `*.out` files:

`K_coefficient.out`

```
> ###
> #####   R SCRIPT for Analysis of
> ###
> #####   - K coefficient
> #####   => ambient/focal
> ###
> …
```

calculated from `amfo.csv`

Gaze analytics pipeline: statistics

Code and output/statistics in the `*.out` files:

`tm.out`

```
> ###
> #####    R SCRIPT for Analysis of
> ###
> #####    - TMs
> #####    - transition entropy
> ###
> …
```

calculated from `fxtn-aois.csv`

Effect of facial emotional expression on traditional and advanced gaze analytics:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:
   - Absolute dwell time, number of fixations
   - Frequency of the initial fixation after stimulus onset
   - Number of transition between AOIs

2) Measures of scanning behavior in general:
   - Absolute number of fixations, duration of fixations
   - pICA
   - K coefficient (ambient / focal fixations)
   - Microsaccades (rate, amplitude)

3) Transition matrices and transition entropy

traditional

advanced

Gaze analytics pipeline: statistics

For the results look for statistics in the `*.out` files:

```
> #####.
> #####. ANOVA - Effect of ttype (emotion) on fixation number on AOI "left eye"
> #####.
> a <- aov_ez(data = dat_leye, id = 'subj', dv = 'fixCount', within = 'ttype')
> kable(nice(a))


|Effect |df           |MSE  |F        |ges |p.value |
|:------|:------------|:----|:--------|:---|:-------|
|ttype  |3.58, 82.28  |0.33 |8.87 *** |.02 |<.0001  |
> # => sign.
```

… and of course at the figures in `./figs`

→ RESULTS

Effect of facial emotional expression on traditional and advanced gaze analytics:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:
   - Absolute dwell time, number of fixations
   - Frequency of the initial fixation after stimulus onset
   - Number of transition between AOIs

2) Measures of scanning behavior in general:
   - Absolute number of fixations, duration of fixations
   - pICA
   - K coefficient (ambient / focal fixations)
   - Microsaccades (rate, amplitude)

3) Transition matrices and transition entropy

traditional

advanced

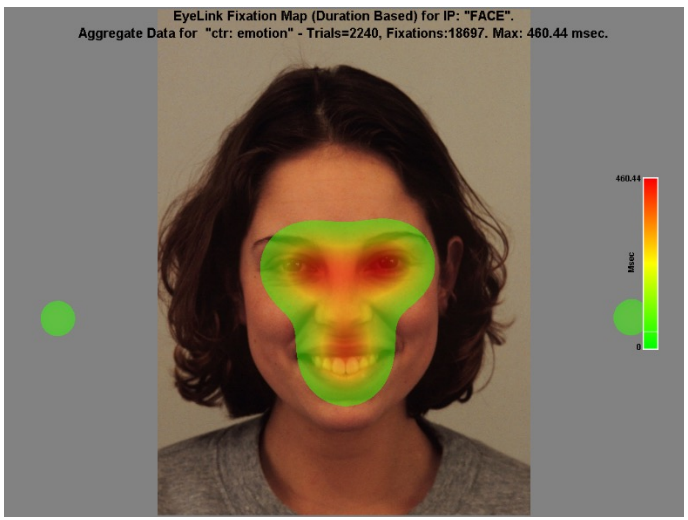
Effect of facial emotional expression – Hypotheses:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:

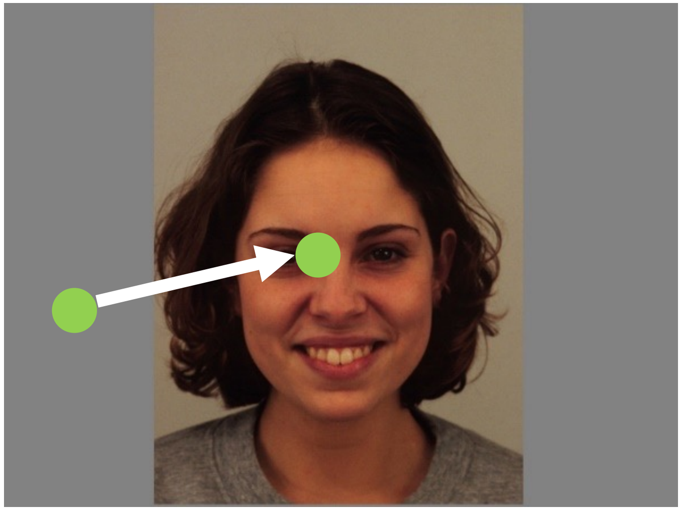
AOIs:
Left eye, right eye,
nose, mouth

Effect of facial emotional expression – Hypotheses:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:
   - <u>Absolute dwell time, number of fixations</u>
   - <u>Frequency of the initial fixation after stimulus onset</u>



→ general attention orienting



→ spontaneous attention orienting

Effect of facial emotional expression – Hypotheses:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:

- <u>Absolute dwell time, number of fixations</u> → General visual attention
- <u>Frequency of the initial fixation after stimulus onset</u>

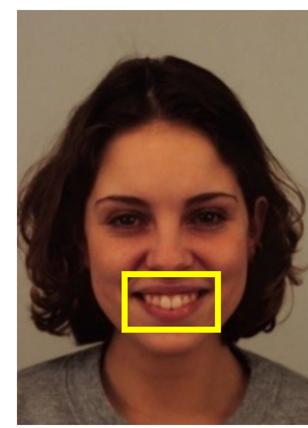
→ Early/spontaneous visual attention

Hypothesis:

- general preference for eye region
- Effect of emotion

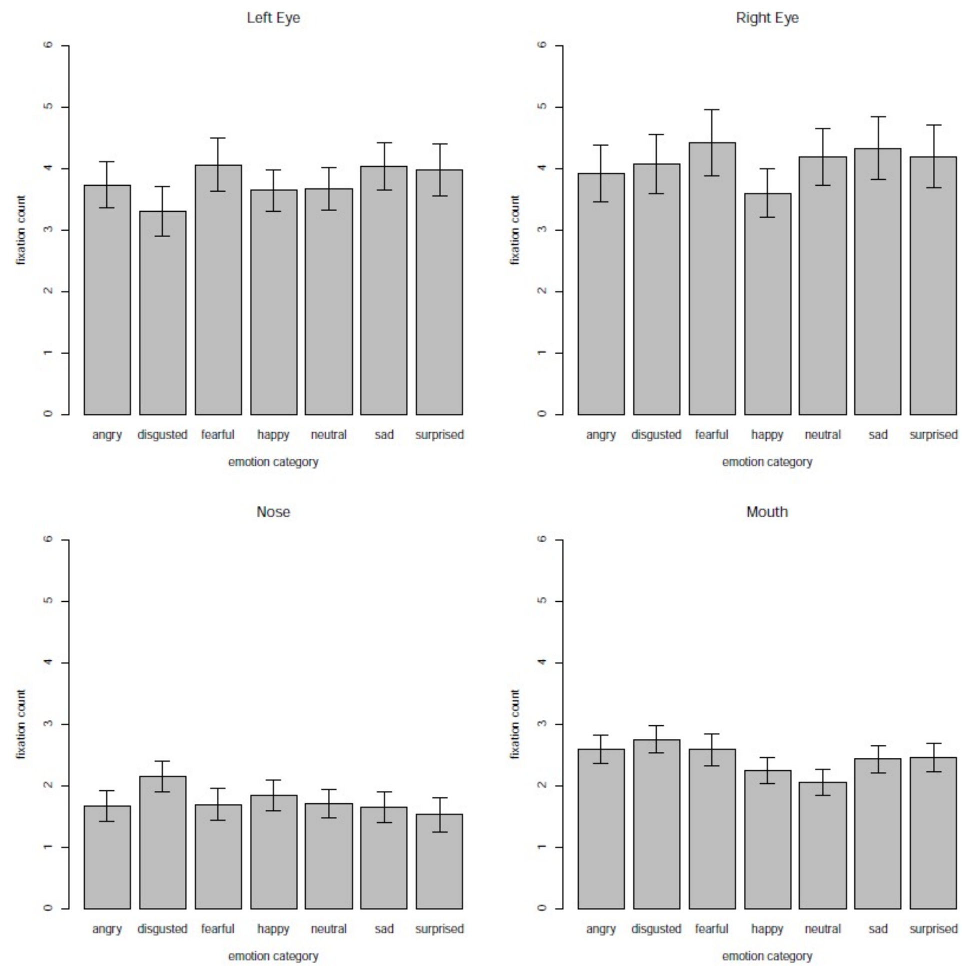
→ Tendency for more attention to diagnostic regions of facial expressions:





Gaze analytics pipeline: figures

- Number of fixations on AOIs “left eye”, “right eye”, “nose”, “mouth” for all emotion categories (ttype)

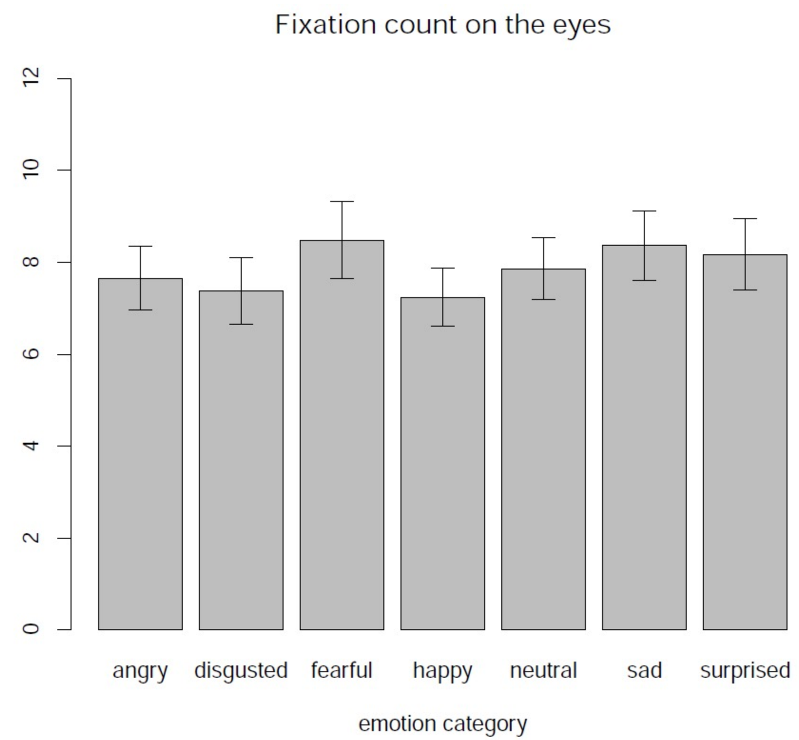


`fixationCount_AOI.pdf`

Gaze analytics pipeline: figures

- Number of fixations on AOI "BOTH EYES" for all emotion categories (ttype)

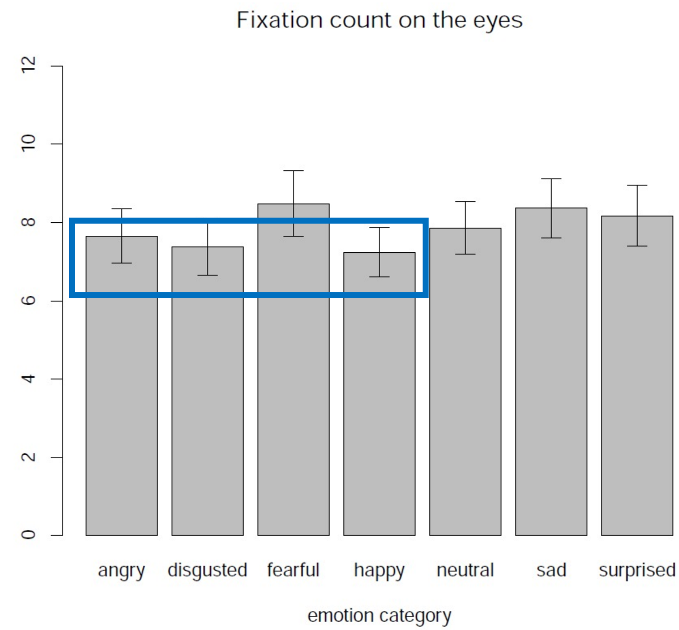
fixationCount_EYES.pdf



Effect	df	MSE	F	ges	p.value
ttype	2.85, 65.59	0.95	12.36 ***	.02	<.0001

Gaze analytics pipeline: figures

- Number of fixations on AOI "BOTH EYES" for all emotion categories (ttype)

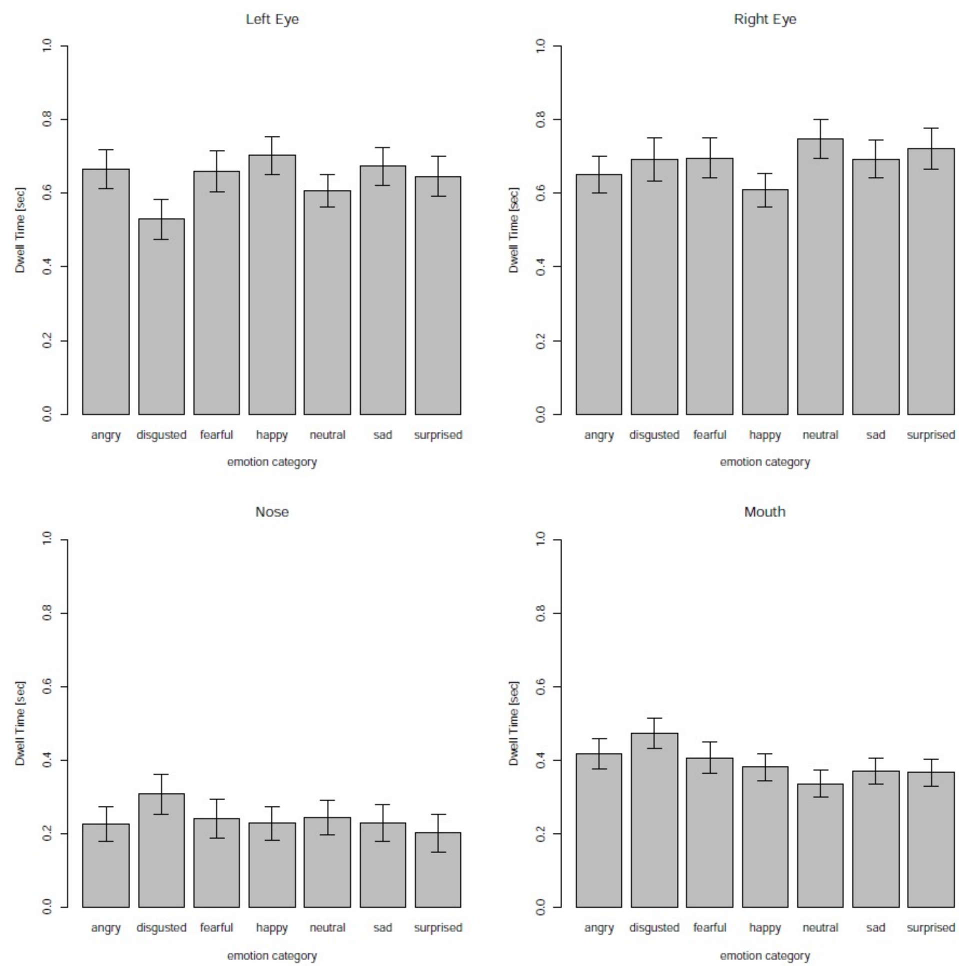


	angry	disgusted	fearful	happy	neutral	sad
disgusted	0.49071	-	-	-	-	-
fearful	0.00395	2.6e-05	-	-	-	-
happy	0.27118	1.00000	0.00396	-	-	-
neutral	1.00000	0.07723	0.13390	0.01366	-	-
sad	0.00022	5.4e-06	1.00000	0.00045	0.07537	-
surprised	0.27118	0.00464	0.49071	0.06040	1.00000	1.00000

Gaze analytics pipeline: figures

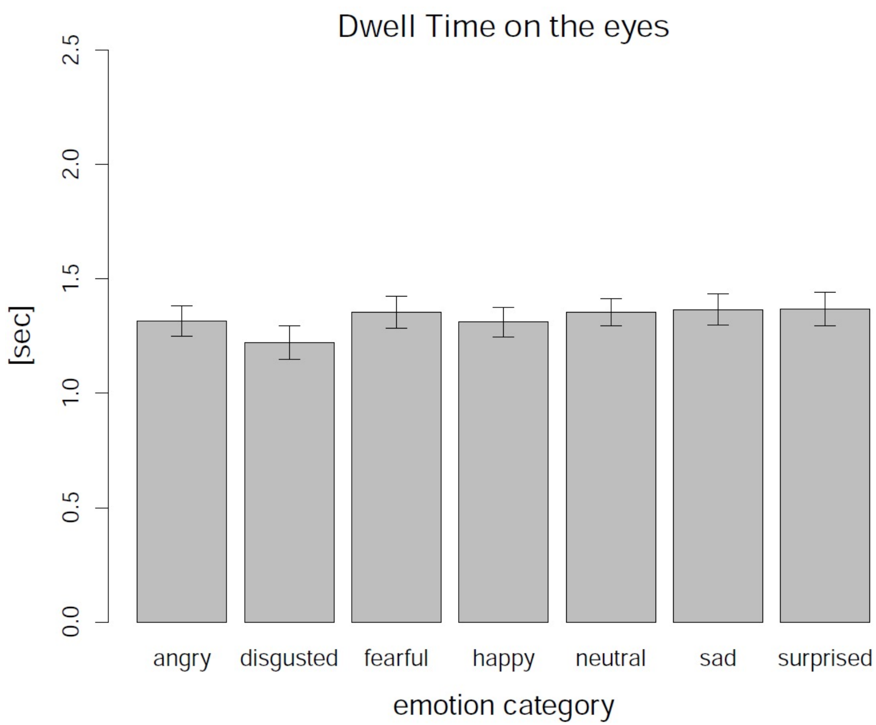
- Absolute dwell time on AOIs “left eye”, “right eye”, “nose”, “mouth” for all emotion categories (ttype)

`dwelltime_AOI.pdf`



Gaze analytics pipeline: figures

- Absolute dwell time on AOI "BOTH EYES" for all emotion categories (ttype)

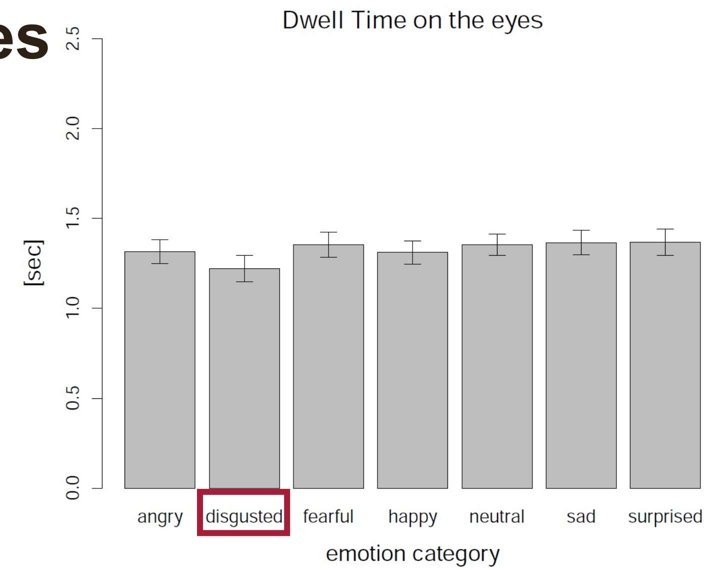


`dwelltime_EYES.pdf`

Effect	df	MSE	F	ges	p.value
ttype	3.60, 82.79	0.01	8.31 ***	.02	<.0001

Gaze analytics pipeline: figures

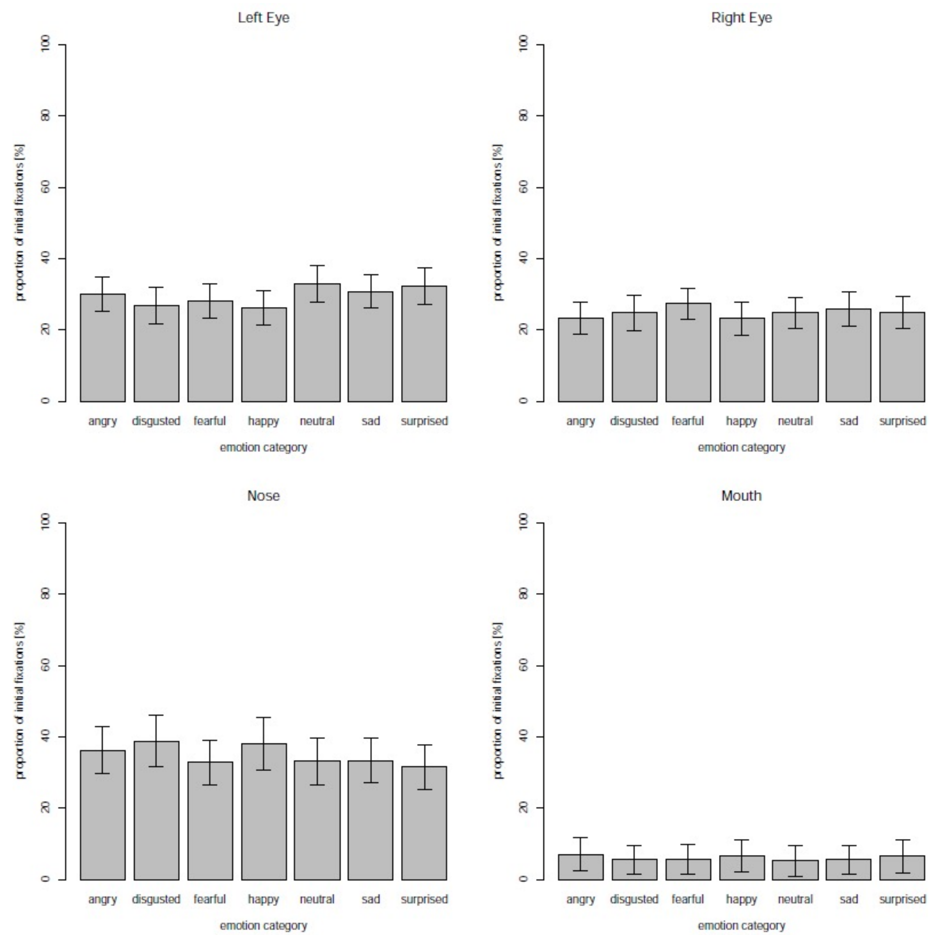
- Absolute dwell time on AOI "BOTH EYES" for all emotion categories (ttype)



	angry	disgusted	fearful	happy	neutral	sad
disgusted	0.00269	-	-	-	-	-
fearful	0.61764	0.00018	-	-	-	-
happy	1.00000	0.13647	1.00000	-	-	-
neutral	0.89029	0.00165	1.00000	0.89029	-	-
sad	0.25152	5.5e-05	1.00000	1.00000	1.00000	-
surprised	0.30520	0.00071	1.00000	1.00000	1.00000	1.00000

Gaze analytics pipeline: figures

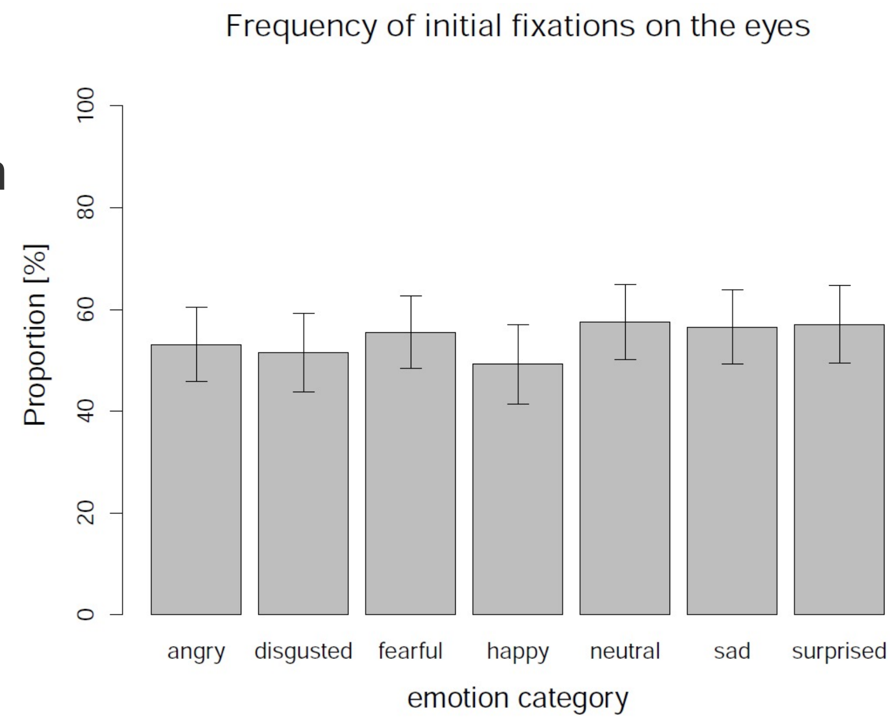
- Frequency of initial fixation after stimulus onset on AOIs “left eye”, “right eye”, “nose”, “mouth” for all emotion categories (ttype)



`initialFixation_AOI.pdf`

Gaze analytics pipeline: figures

- Frequency of initial fixation after stimulus onset on AOI "BOTH EYES" for all emotion categories (ttype)



`initialFixation_EYES.pdf`

Effect	df	MSE	F	ges	p.value
ttype	4.23, 97.33	112.52	2.97 *	.007	.02

Effect of facial emotional expression – Hypotheses:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:

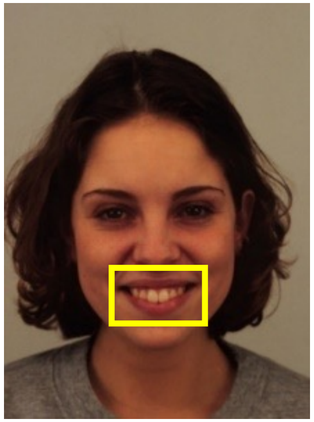
- Absolute dwell time, number of fixations → General visual attention
- Frequency of the initial fixation after stimulus onset → Early/spontaneous visual attention

Hypothesis:

- general preference for eye region
- Effect of emotion

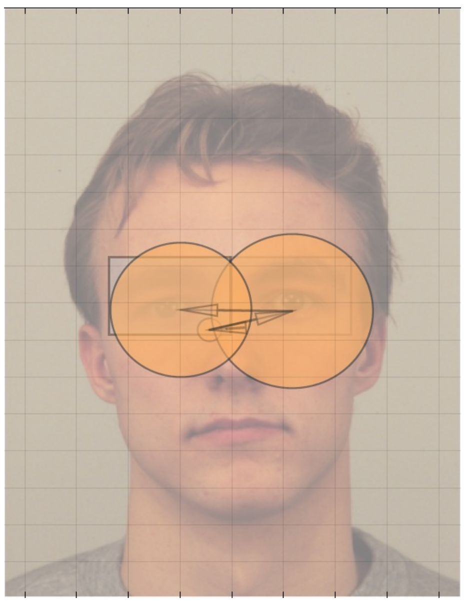
→ Tendency for more attention to diagnostic regions of facial expressions:



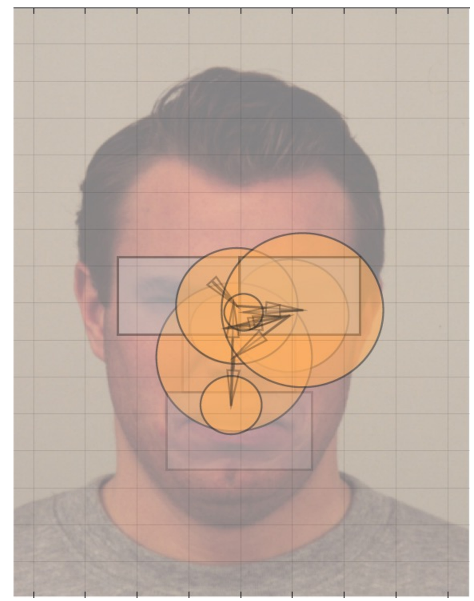


Effect of facial emotional expression – Hypotheses:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:
   - Number of transitions between AOIs → Extent of exploration



→ Few transitions



→ Many transitions

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Gaze analytics pipeline:

AOIs:
Left eye, right eye, nose, mouth

Prior to this analysis, it is useful to check how many fixations are within the pre-defined AOIs in order to verify their definition as interesting regions.
Do we include most of the fixations in the following analysis?
If not, we may have forgotten a relevant region of the stimulus.

This time, we include 97.76% of the fixations!

Effect of facial emotional expression – Hypotheses:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:

- Number of transition between AOIs → Extent of exploration

2) Measures of scanning behavior in general:

- Absolute number of fixations, duration of fixations

→ Associated with extent of exploration

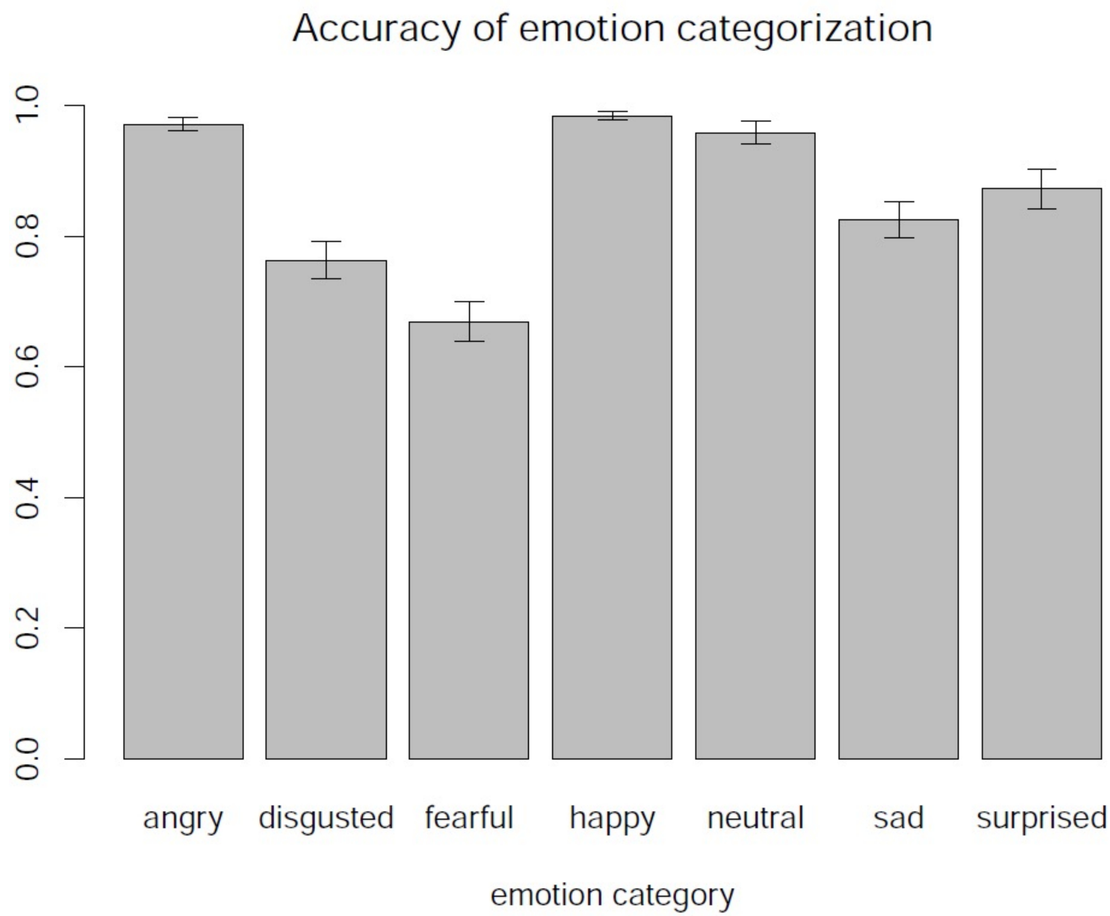
→ Inversely correlated with number of fixations

Hypothesis:

- Difficulty ↑ Extent of exploration ↑ → Positive relationship
- Difficulty ↑ Absolute fixation number ↑
- Absolute fixation number ↓ Mean fixation duration ↑

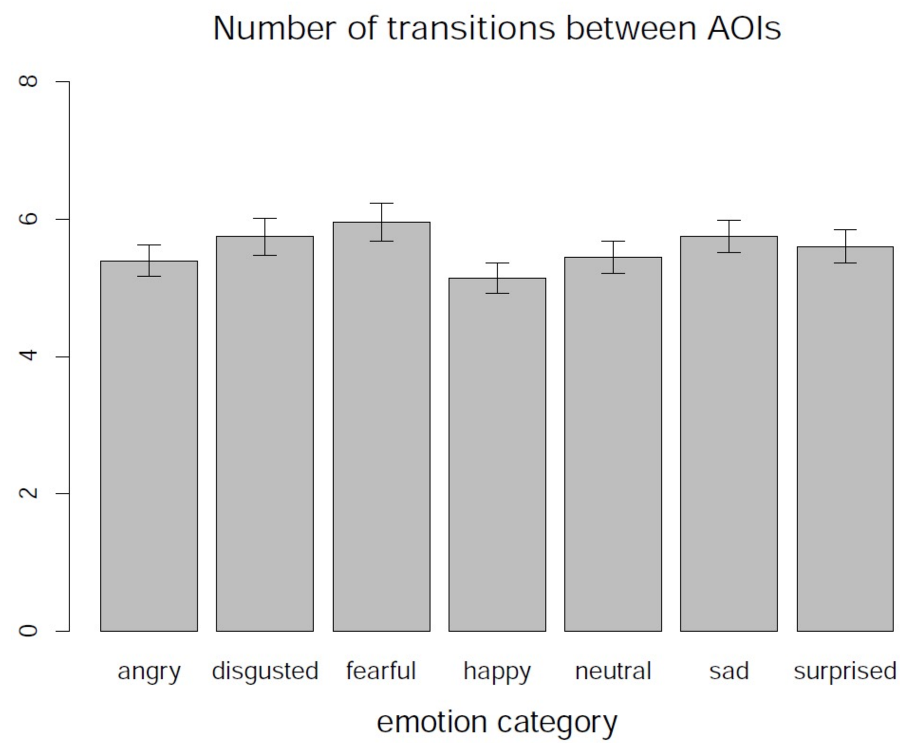
Gaze analytics pipeline: figures

- Difficulty



Gaze analytics pipeline: figures

- Number of transitions between AOIs for all emotion categories (ttype)

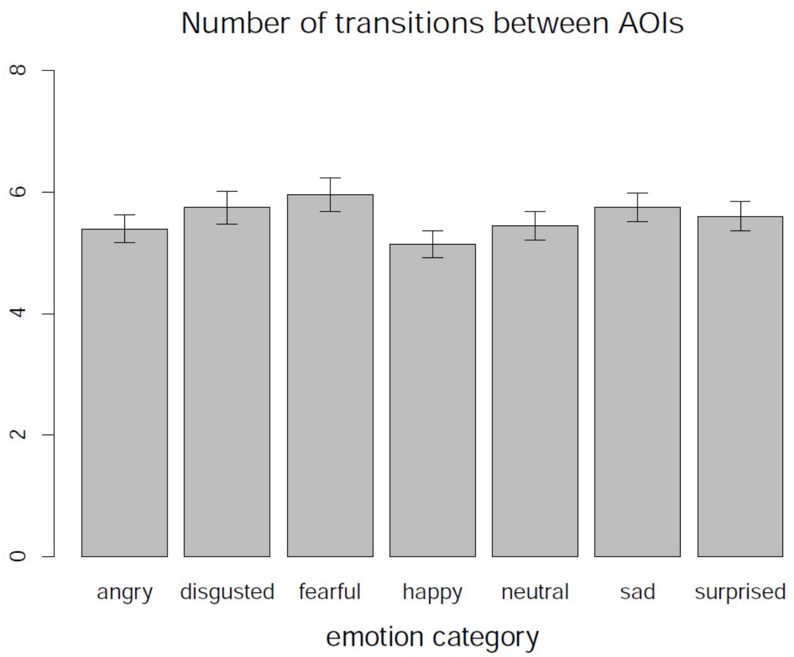


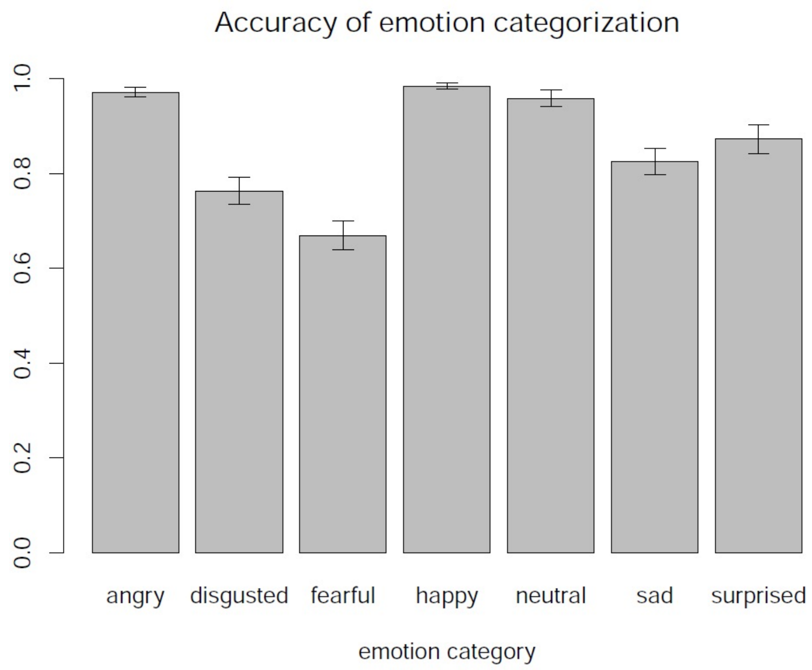
`transitionCount.pdf`

```
|Effect |df            |MSE  |F         |ges |p.value |
|:------|:-------------|:----|:---------|:---|:-------|
|ttype  |4.99, 114.72  |0.20 |10.51 *** |.04 |<.0001  |
```

Gaze analytics pipeline: figures

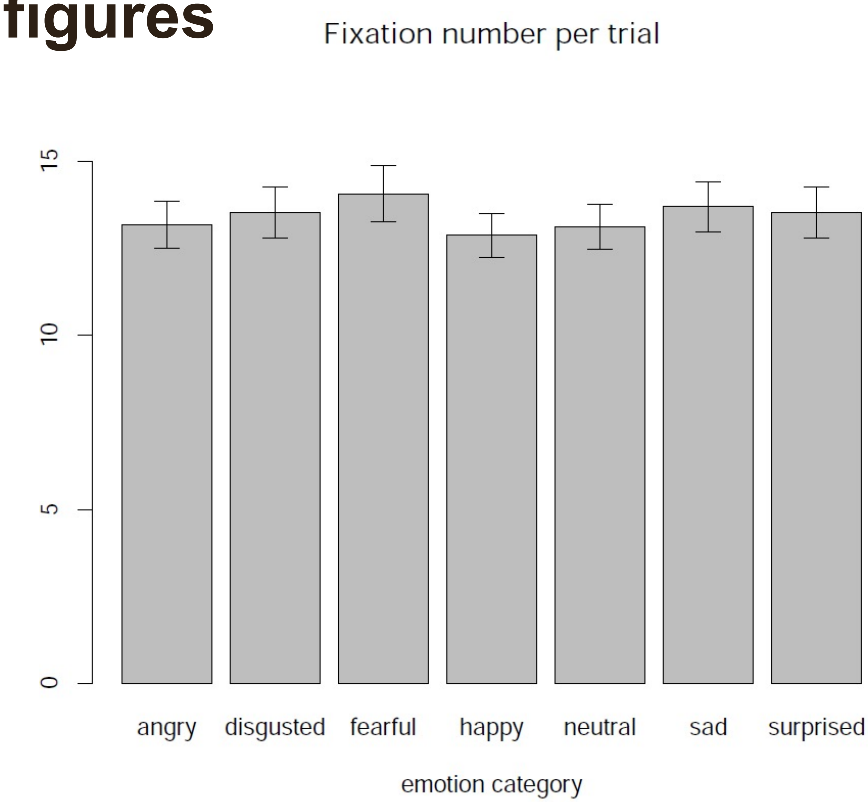
Direct comparison with accuracy data of emotion categorization task:





Gaze analytics pipeline: figures

- Number of fixations for all emotion categories (ttype)



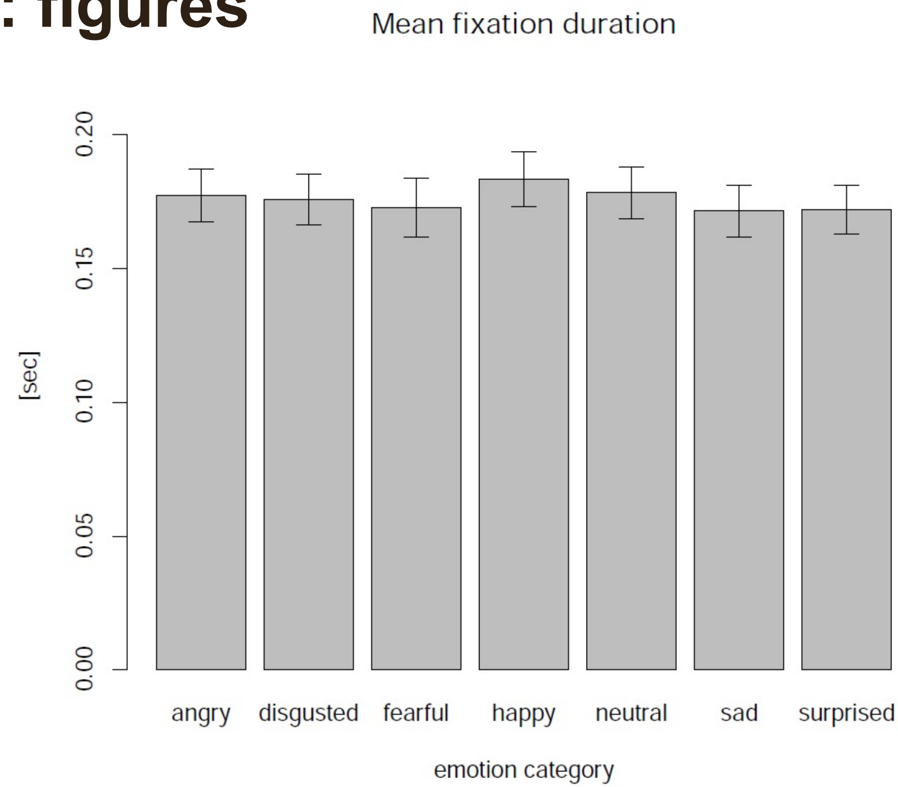
`fixation number per trial.pdf`

Effect	df	MSE	F	ges	p.value
ttype	3.65, 84.01	0.79	8.00 ***	.01	<.0001

Gaze analytics pipeline: figures

- Mean fixation duration for all emotion categories (ttype)

`fixation duration.pdf`



Effect	df	MSE	F	ges	p.value
ttype	3.46, 79.54	0.00	2.82 *	.007	.04

Effect of facial emotional expression – Hypotheses:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:

- Number of transition between AOIs → Extent of exploration

2) Measures of scanning behavior in general:

- Absolute number of fixations, duration of fixations

→ Associated with extent of exploration

→ Inversely correlated with number of fixations

Hypothesis:

- Difficulty ↑ Extent of exploration ↑ → Positive relationship
- Difficulty ↑ Absolute fixation number ↑
- Absolute fixation number ↓ Mean fixation duration ↑

Effect of facial emotional expression on traditional and advanced gaze analytics:

1) Measures related to Areas of Interest (AOIs) such as the eyes of the faces:
   - Absolute dwell time, number of fixations
   - Frequency of the initial fixation after stimulus onset
   - Number of transition between AOIs

2) Measures of scanning behavior in general:
   - Absolute number of fixations, duration of fixations
   - pICA
   - K coefficient (ambient / focal fixations)
   - Microsaccades (rate, amplitude)

3) Transition matrices and transition entropy

traditional

advanced

Effect of facial emotional expression – Hypotheses:

2) Measures of scanning behavior in general:

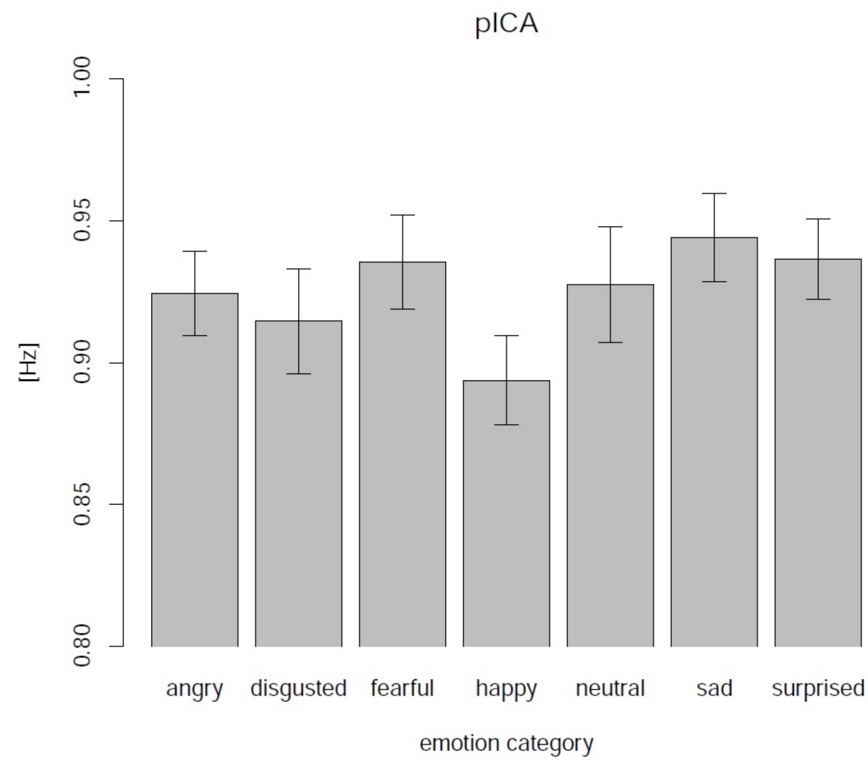
- pICA
- K coefficient (ambient / focal fixations)
- Microsaccades (rate, amplitude)

→ No specific hypotheses in this experiment.
But we show the explorative analysis to present these advanced gaze analytic methods.

Gaze analytics pipeline: figures

- pICA for all emotion categories (ttype)

`pICA.pdf`

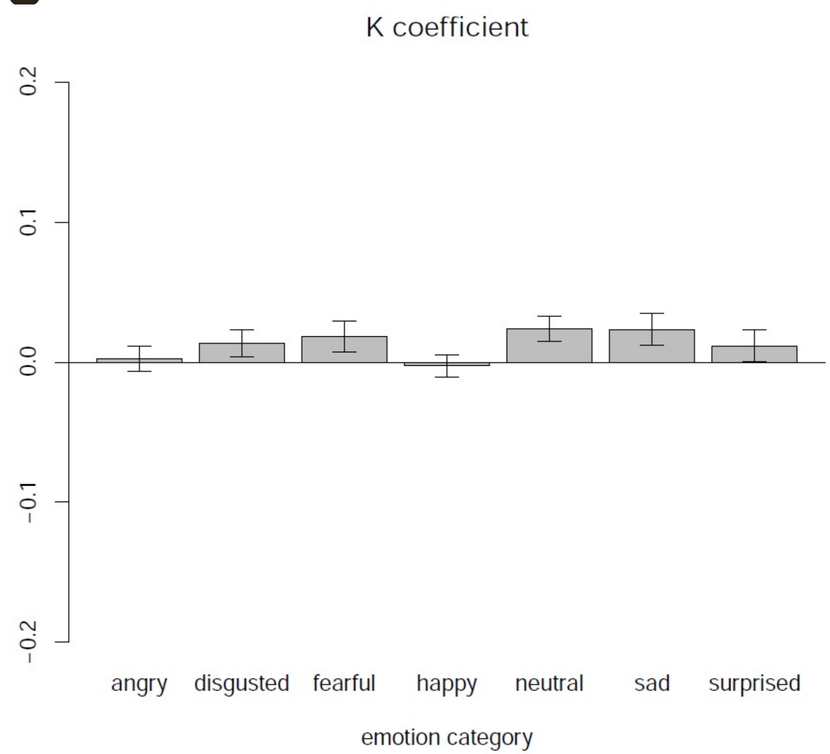



```
|Effect |df           |MSE  |F    |ges |p.value |
|:------|:------------|:----|:----|:---|:-------|
|ttype  |4.16, 95.63  |0.01 |1.42 |.04 |.23     |
```

Gaze analytics pipeline: figures

- K coefficient (ambient/focal fixations) for all emotion categories (ttype)

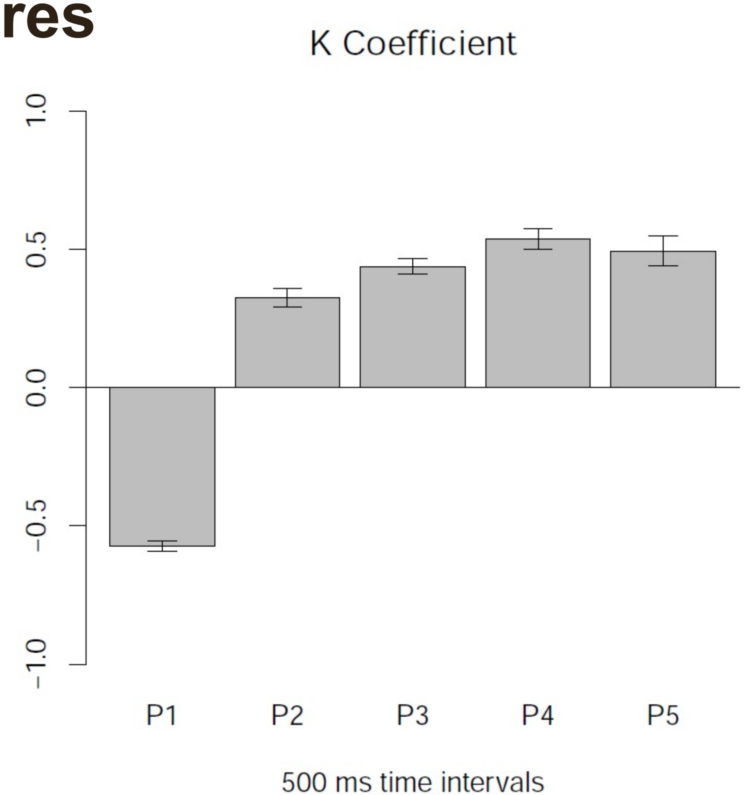
`K_coefficient.pdf`



Effect	df	MSE	F	ges	p.value
ttype	4.85, 111.63	0.00	1.92 +	.04	.10

Gaze analytics pipeline: figures

- K coefficient (ambient/focal fixations) for time intervals of 500 ms

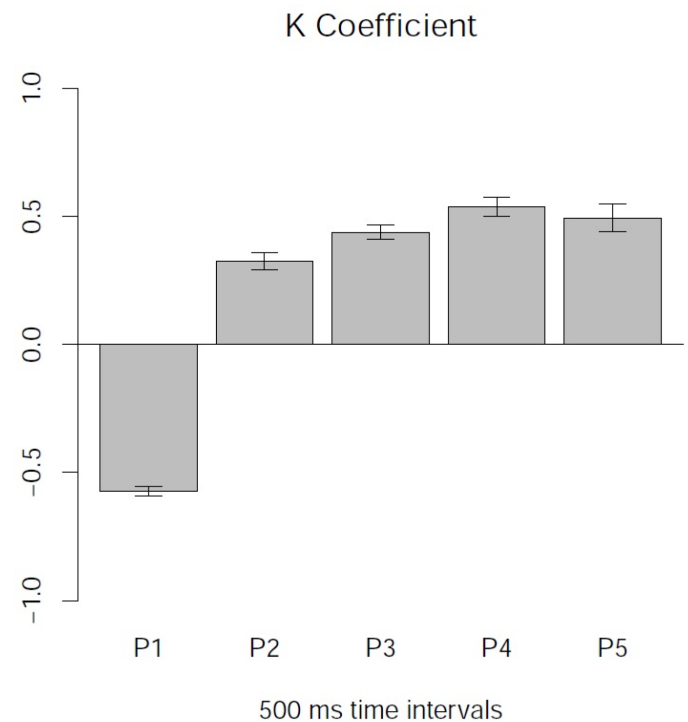


K_coefficient_
timecut5.pdf

Effect	df	MSE	F	ges	p.value
timecut.5	2.13, 49.02	0.05	204.10 ***	.85	<.0001

Gaze analytics pipeline: figures

- K coefficient (ambient/focal fixations) for time intervals of 500 ms

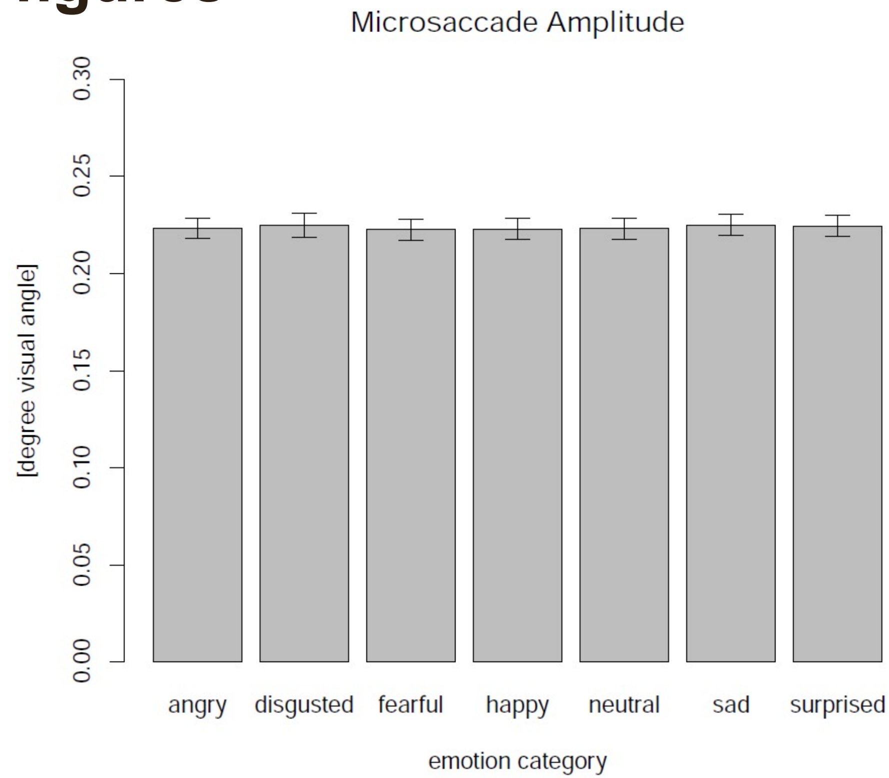


Remember the experimental design:

+ 500 ms time intervals might be too short

Gaze analytics pipeline: figures

- Microsaccade amplitude for all emotion categories (ttype)



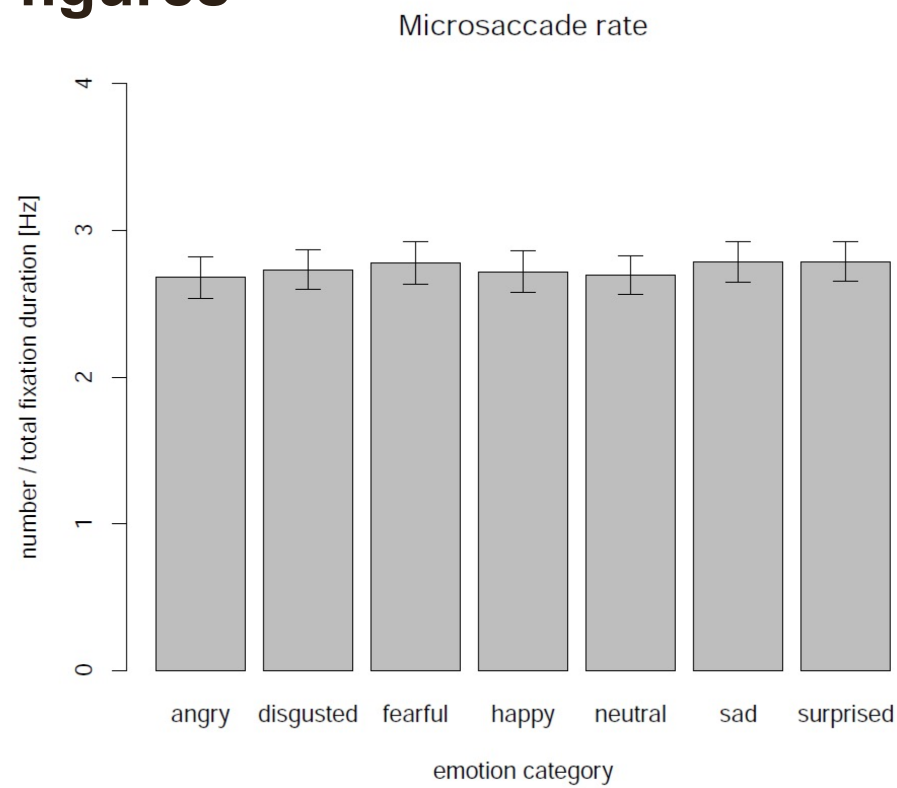
msamp.pdf

Effect	df	MSE	F	ges	p.value
ttype	4.67, 107.41	0.00	0.32	.001	.89

Gaze analytics pipeline: figures

- Microsaccade rate for all emotion categories (ttype)

msrt.pdf



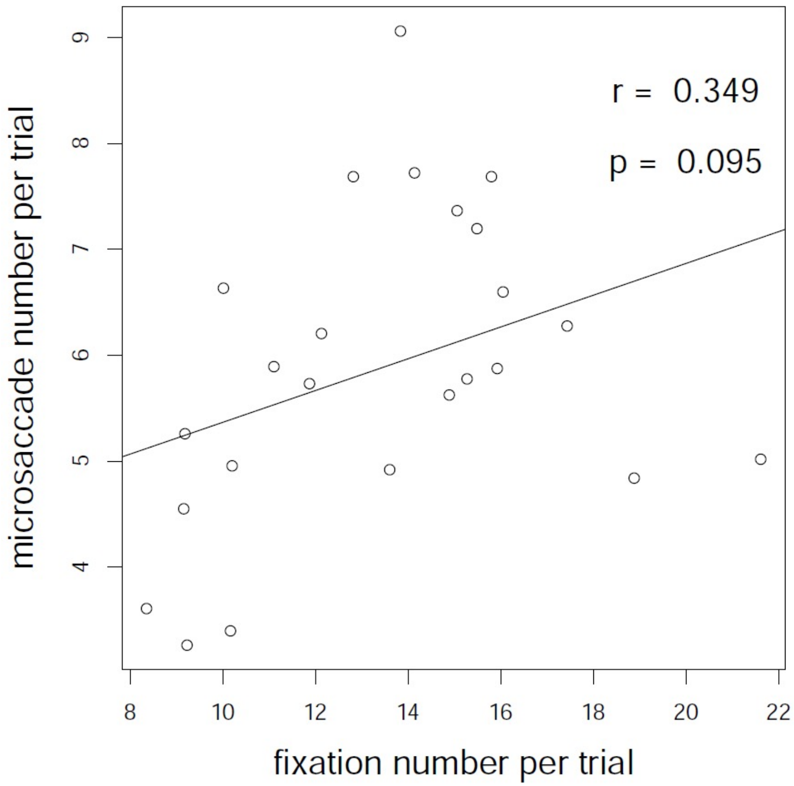
Effect	df	MSE	F	ges	p.value
ttype	4.08, 93.78	0.06	1.28	.004	.28

Gaze analytics pipeline: Microsaccades and Fixations

BE AWARE OF ASSOCIATION of MICROSACCADES AND FIXATIONS!

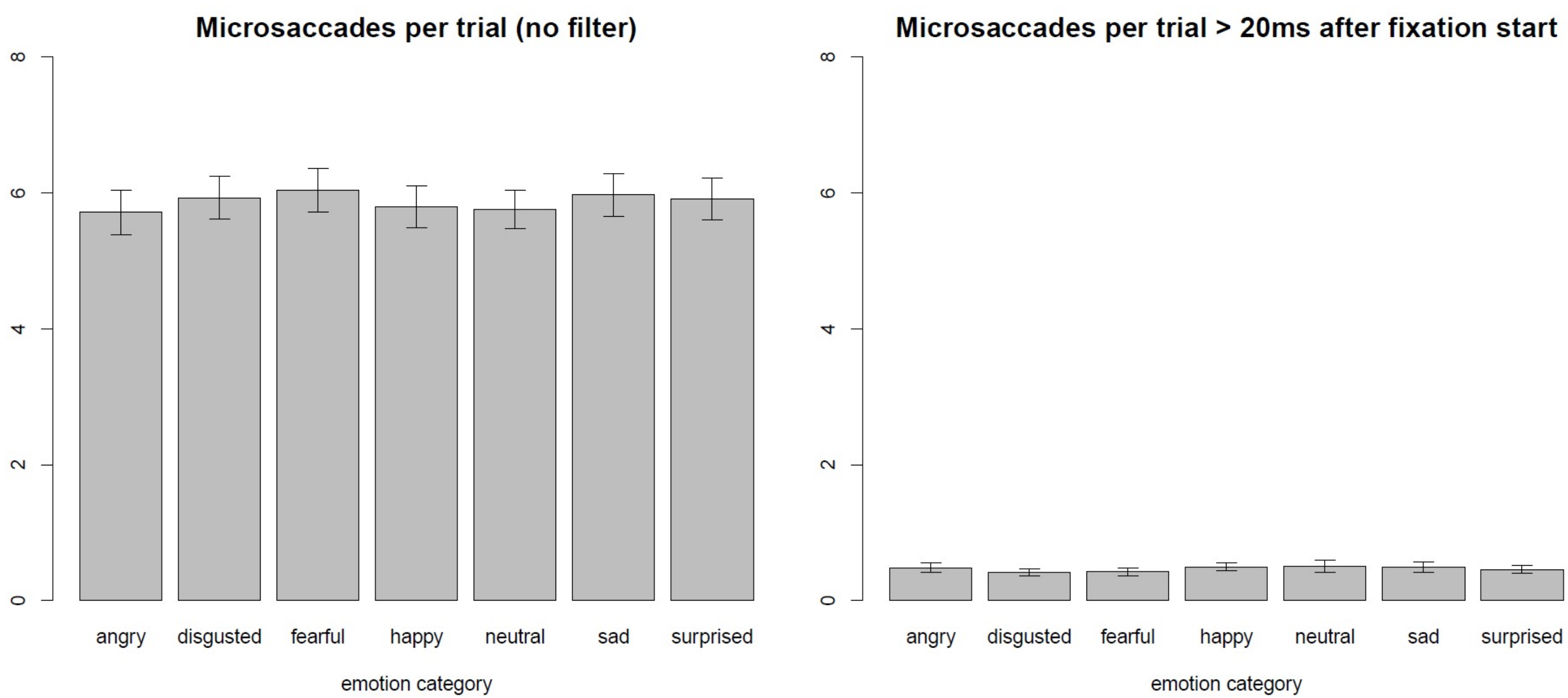
$$microsaccade\ rate\ for\ one\ trial = \frac{N_{microsaccades}}{Duration_{F1} + Duration_{F2} + etc.}$$

Gaze analytics pipeline: Microsaccades and Fixations



Gaze analytics pipeline: microsaccades

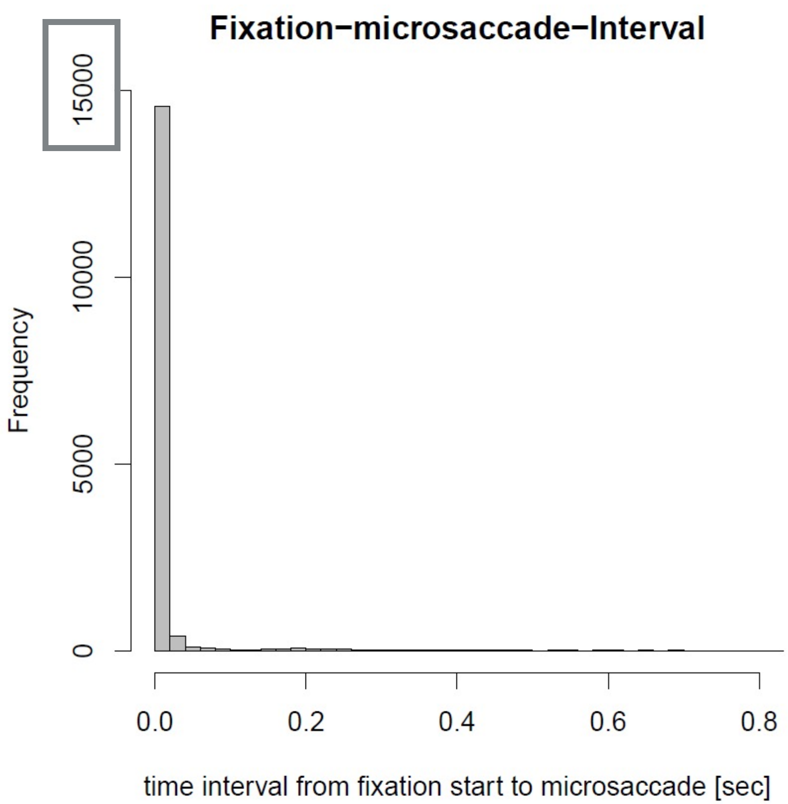
- Number of microsaccades per trial

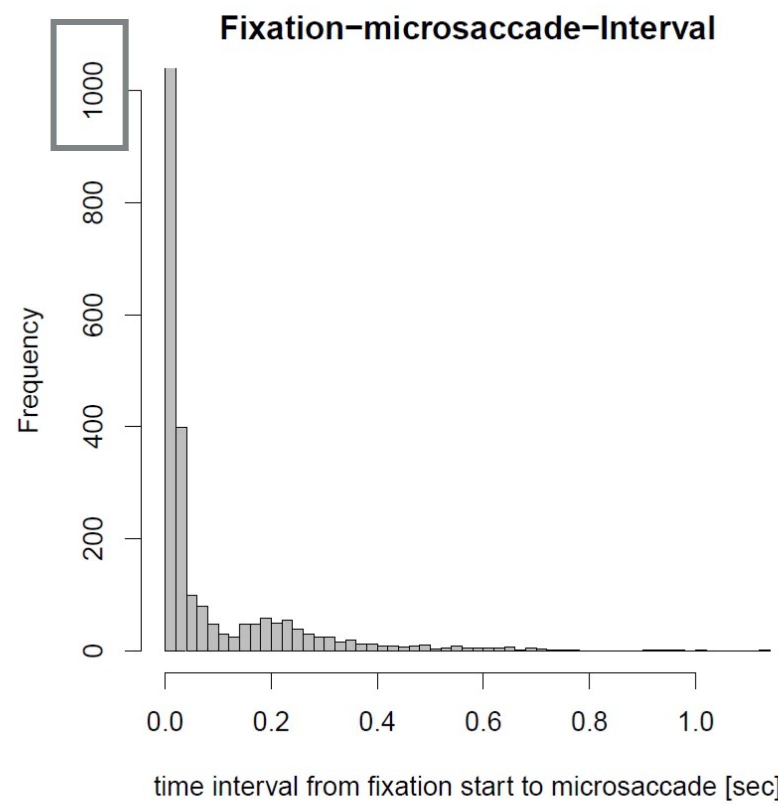


Gaze analytics pipeline: microsaccades

Gaze analytics pipeline: microsaccades

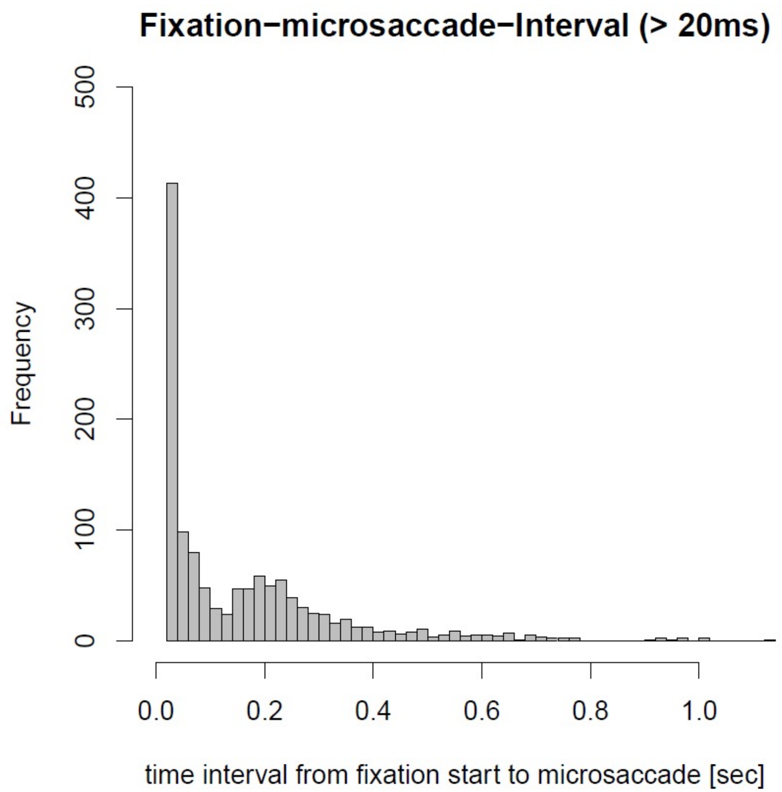
- Histograms

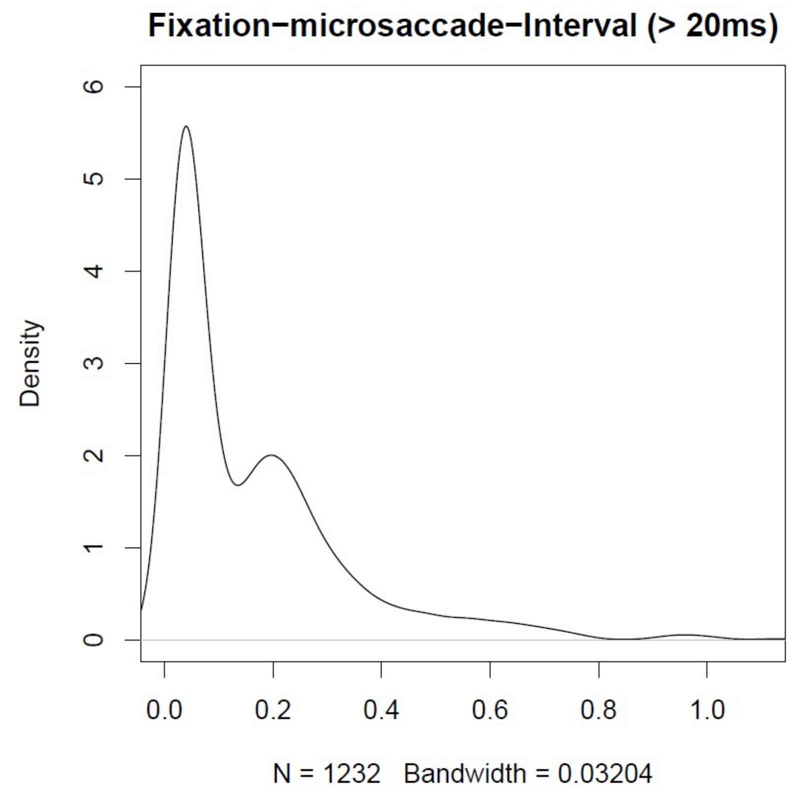




Gaze analytics pipeline: microsaccades

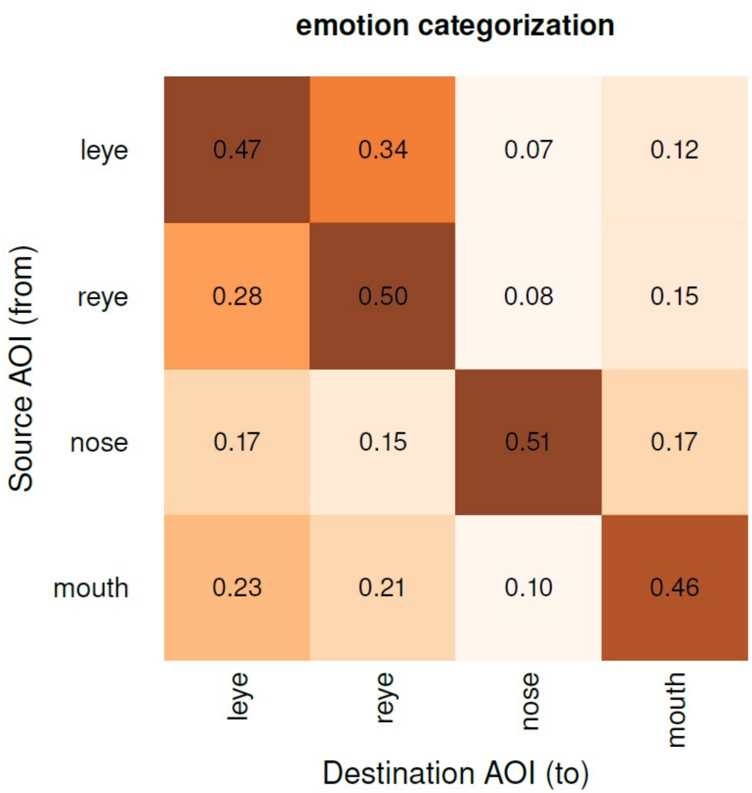
- Without microsaccades within 20ms after fixation start

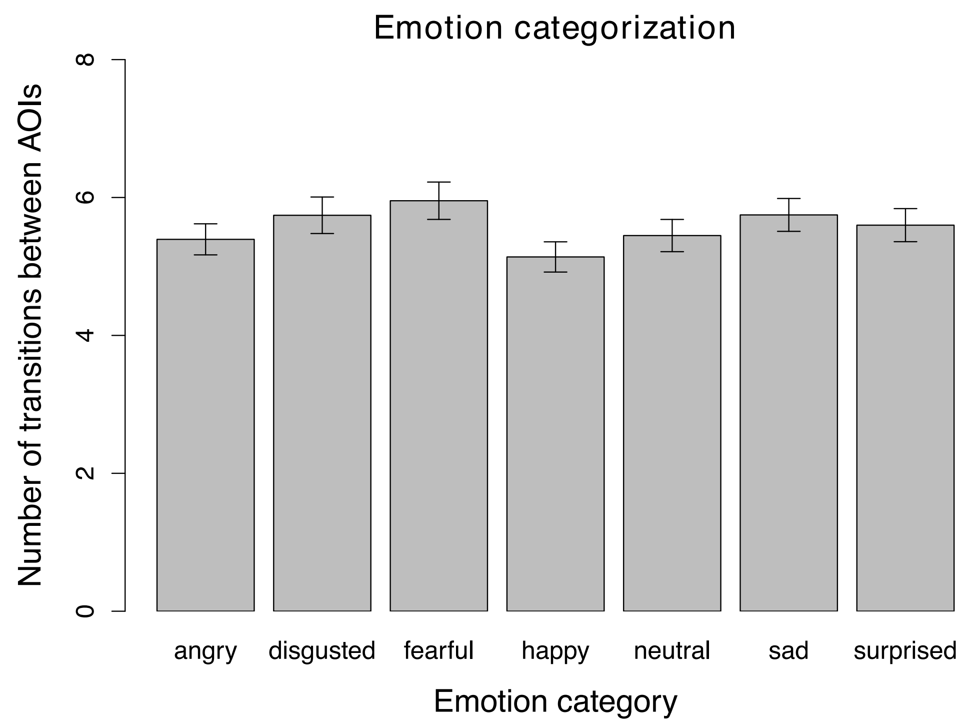




Gaze analytics pipeline: transition count

- Transition matrix overall and number of transitions per condition

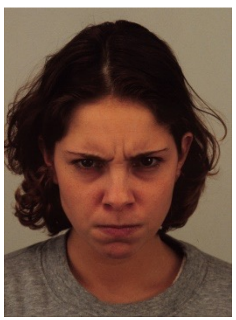


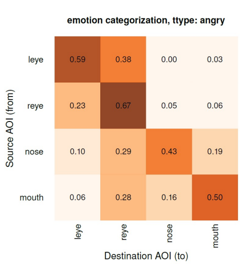


Gaze analytics pipeline: transition entropy

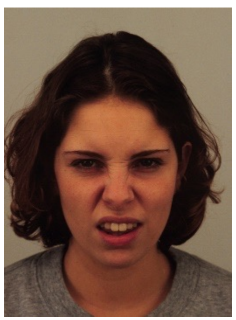
- Want to compare transition matrices between conditions

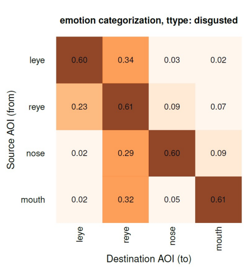
angry



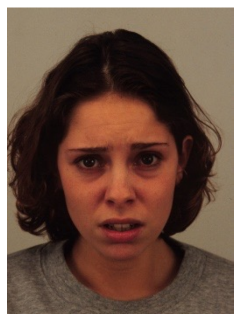


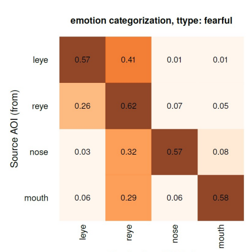
disgusted



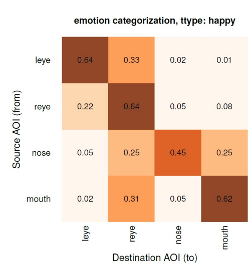


fearful

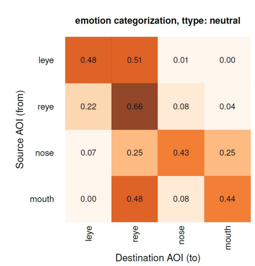




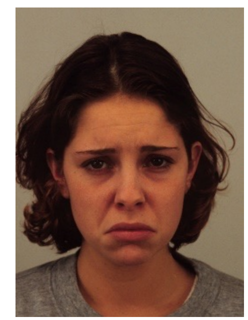
happy

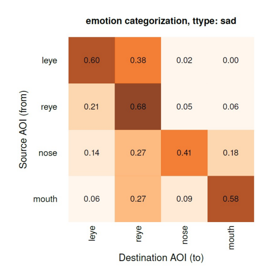


neutral

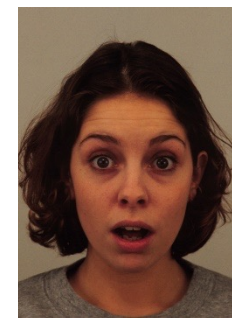


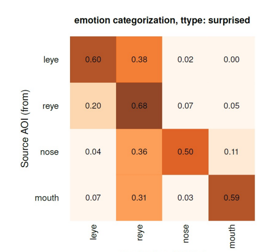
sad





surprised

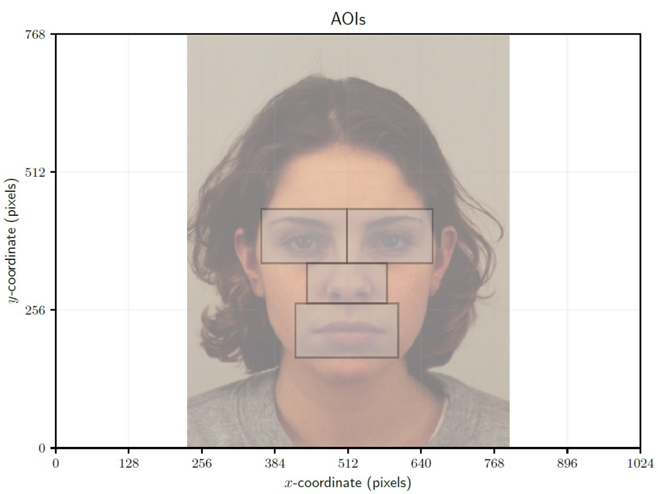




Gaze analytics pipeline: transition entropy

- Normalized transition entropy

set of AOIs $\mathcal{S} = \{1, \ldots, s\}$



first-order transition matrices

Source AOI (from) \ Destination AOI (to)	leye	reye	nose	mouth
leye	p	p	p	p
reye	p	p	p	p
nose	p	p	p	p
mouth	p	p	p	p

$$H_t = -\frac{1}{\log_2 |\mathcal{S}|} \sum_{i \in \mathcal{S}} p_i \sum_{j \in \mathcal{S}} p_{ij} \log_2 p_{ij}$$

Gaze analytics pipeline: transition entropy

- Normalized transition entropy
- Higher entropy means “surprise!”

$$H_t = 1$$

→ Low predictability

Source AOI (from) \ Destination AOI (to)	leye	reye	nose	mouth
leye	0.25	0.25	0.25	0.25
reye	0.25	0.25	0.25	0.25
nose	0.25	0.25	0.25	0.25
mouth	0.25	0.25	0.25	0.25

$$H_t = 0$$

→ High predictability

Source AOI (from) \ Destination AOI (to)	leye	reye	nose	mouth
leye	0.00	1.00	0.00	0.00
reye	0.00	0.00	1.00	0.00
nose	0.00	0.00	0.00	1.00
mouth	1.00	0.00	0.00	0.00

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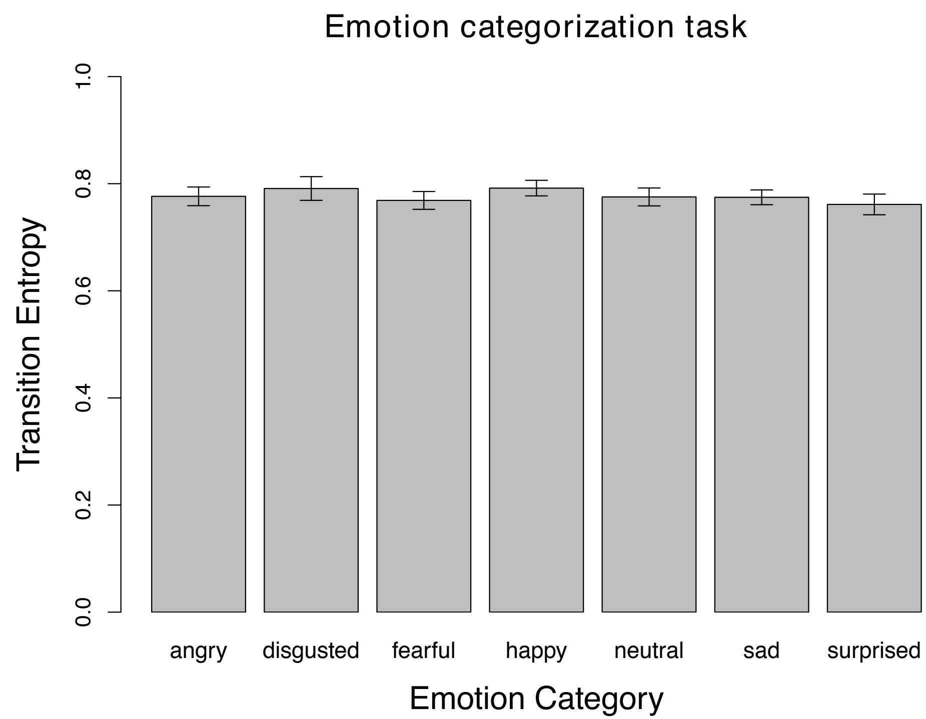
Gaze analytics pipeline: transition entropy

- Normalized transition entropy
- Higher entropy means "surprise!"

$$H_t = -\frac{1}{\log_2 s} \sum_{i \in \mathcal{S}} \pi_i \sum_{j \in \mathcal{S}} p_{ij} \log_2 p_{ij}$$

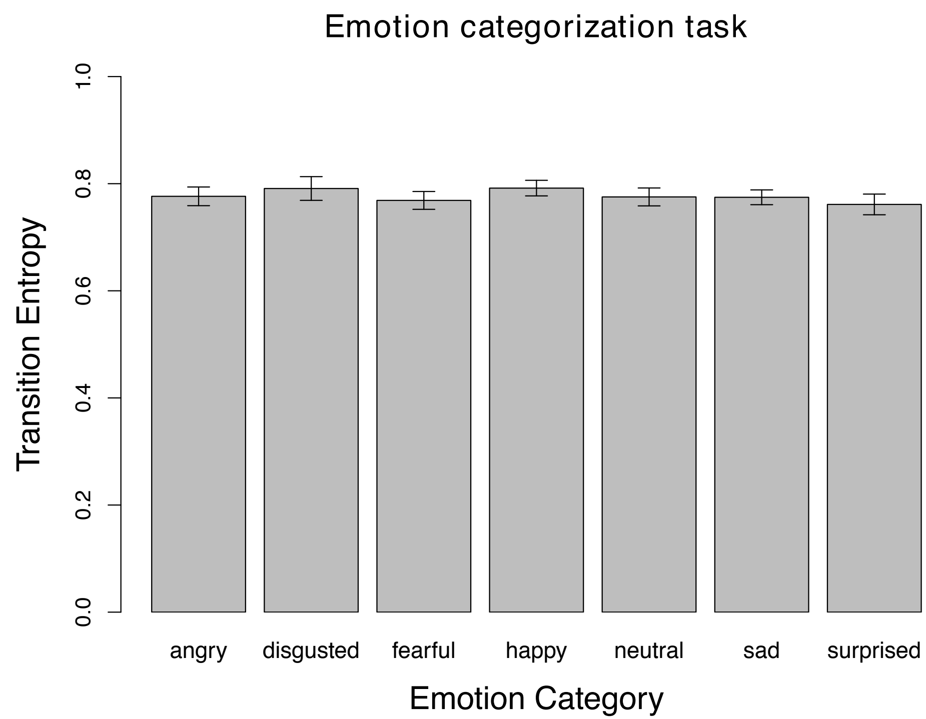


Gaze analytics pipeline: transition entropy

- Normalized transition entropy
- Higher entropy means “surprise!”
- Stationary entropy: long run

$$H_t = -\frac{1}{\log_2 s} \sum_{i \in \mathcal{S}} \pi_i \sum_{j \in \mathcal{S}} p_{ij} \log_2 p_{ij}$$

$$H_s = -\sum_{i \in \mathcal{S}} \pi_i \log \pi_i$$



Stationary entropy: transition vs. stationary entropy?

- Ultimately, not super certain of stationary entropy's utility

- Because:

$$H_t = -\frac{1}{log_2 s} \sum_{i \in \mathcal{S}} \pi_i \sum_{j \in \mathcal{S}} p_{ij} \log_2 p_{ij} \qquad H_s = -\sum_{i \in \mathcal{S}} \pi_i \log \pi_i$$

$$H_t \leq H_s$$

transition entropy is always smaller

- Long-term distribution of transitions is expected to be more uniform

Gaze analytics pipeline: where to go from here?

- Important to remember what the pipeline offers: metrics
- Which metrics to use will depend on study **hypothesis**

- General strategy "recipe" for controlled experiments:
  - formulate hypothesis
    - don't start with "I wonder what would happen if..."
    - start with "I bet this would happen if..."
  - design experiment (e.g., within-, between-subjects)
  - choose metrics
    - gaze metrics (process metrics) often supplement performance metrics
  - choose analytical tools (stats, e.g., ANOVA, something else)

- Can do exploratory research or pilot studies beforehand

Gaze analytics pipeline: write paper

- Remember analytics pipeline is meant to help automate analysis
- Once that’s done, write the paper
- This too has a basic “recipe”:
  - abstract, intro, background
  - hypothesis
    - recent trend is to register this a priori
  - methodology
    - design, stimulus, apparatus, procedure, participants
  - results
  - discussion
  - conclusions

Implementing Innovative Gaze Analytic Methods in Clinical Psychology

A Study on Eye Movements in Antisocial Violent Offenders

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ABSTRACT

A variety of psychological disorders like antisocial personality disorder have been linked to impairments in facial emotion recognition. Exploring eye movements during categorization of emotional faces is a promising approach with the potential to reveal possible differences in cognitive processes underlying these deficits. Based on this premise we investigated whether antisocial violent offenders exhibit different scan patterns compared to a matched healthy control group while categorizing emotional faces. Group differences were analyzed in terms of attention to the eyes, extent of exploration behavior and structure of switching patterns between Areas of Interest. While we were not able to show clear group differences, the present study is one of the first that demonstrates the feasibility and utility of incorporating recently developed eye movement metrics such as gaze transition entropy into clinical psychology.

CCS CONCEPTS

• **Applied computing → Psychology**;

KEYWORDS

eye tracking, antisocial offenders, facial emotion recognition

ACM Reference format:
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1 INTRODUCTION

The ability to decode nonverbal social information in order to infer the emotional state of an interaction partner is crucial for effective social interaction. Accordingly, individuals are able to quickly and efficiently identify emotional expressions from specific facial cues [Smith et al. 2005; Tracy and Robins 2008]. These cues are similar across cultures, at least for the six basic emotions, i.e., anger, disgust, fear, happiness, sadness, and surprise [Ekman 1999; Ekman and Friesen 1971]. The accurate interpretation of emotional expressions is based on the processing of relevant regions of the face and directing visual attention to them (e.g., wide-open fearful eyes or smiling happy mouth) [Eisenbarth and Alpers 2011; Schurgin et al. 2014]. Thus, tracking eye movements while viewing emotional faces is a promising approach to gain insight into the processes underlying categorization of emotions.

In clinical research, eye tracking can be a useful tool to explore deviations in scanning patterns that could account for emotion recognition impairments associated with psychological disorders. Impairments in facial affect recognition have been linked to the development and maintenance of various psychological disorders including autism [Uljarevic and Hamilton 2013], depression [Dalili et al. 2015], anxiety disorders [Demenescu et al. 2010], schizophrenia [Kohler et al. 2009], attention-deficit hyperactivity disorder [Bora and Pantelis 2016], and antisocial personality disorder (ASPD) and psychopathy [Dawel et al. 2012; Marsh and Blair 2008].

The majority of clinical studies exploring eye movements while viewing faces does not tap the potential of the myriad analytical methods available. Although analysis of dwell time or number of fixations to certain Areas of Interest (AOIs) can yield interesting findings, an inclusion of more innovative and complex analytical methods (e.g., sequential analysis of eye movements) may add valuable information. Here, we present an analysis of scan patterns while viewing faces including widely-used standard eye movement parameters (e.g., total dwell time) as well as more recently developed metrics such as gaze transition entropy [Krejtz et al. 2015]. Based on these measures, we investigate group differences in attention orienting to the eyes, extent of exploration behavior and structure of switching patterns between AOIs in antisocial violent offenders (AVOs) and a matched healthy control group.