

Eye Tracking Data Classification

Thesis presentation

Alexander Steg

May 19, 2014

Computer Science Dept. 5 (Pattern Recognition)

Friedrich-Alexander University Erlangen-Nuremberg



FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG

TECHNISCHE FAKULTÄT



Eye Tracking Data Classification

- Motivation
- Eye Tracking
- Experimental Setup - Theory
- Experimental Setup - Application
- Results
- Conclusion

Motivation

Eye Tracking

Definition:

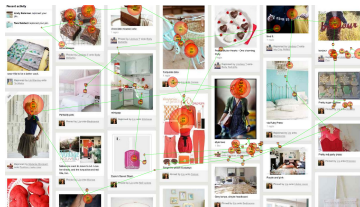
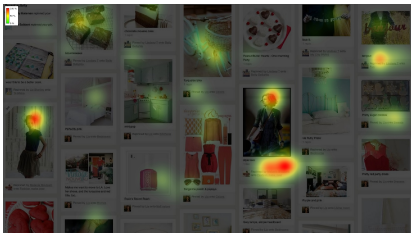
Eye Tracking is the recording of the movement of the eye.

Use of eye tracking

- Optimize advertisements/websites/product label designs.
- User interface for disabled persons.
- Medical/ Psychological research

Both Apple and Google patented eye tracking applications in the year 2013.

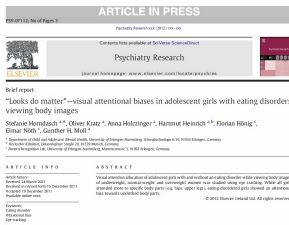
Eye Tracking



Source: www.eyegaze.com

“Looks do matter” – visual attentional biases in adolescent girls with eating disorders viewing body images

Eye tracking study by Horndasch et al.



- analyzed the gaze behavior of 42 adolescent girls with and without eating disorders via eye tracking
- viewed pictures of underweight, normal-weight and overweight women

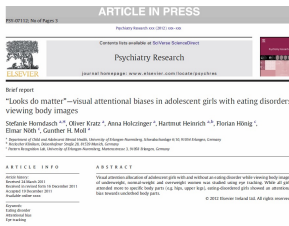
Article by Horndasch et al.

“Looks do matter” – visual attentional biases in adolescent girls with eating disorders viewing body images

Eye tracking study by Horndasch et al.

Conclusion of the article:

- patients with eating disorder fixated more at unclothed body parts compared to normal controls
- “Index body parts” did not draw visual attention of eating-disordered patients to a greater extend then that of healthy controls.



Article by Horndasch et al.

Aims of this Thesis

- Literature overview of the fundamentals of the eye, eye tracking and eye tracking principles.
- Literature overview over the feature extraction and selection.
- Development of the feature extraction for eye tracking and implementation in the “Eye Tracking Tool”.
- Evaluation of the extracted features compared to the data of Horndasch et al.

Eye Tracking

The Human Eye

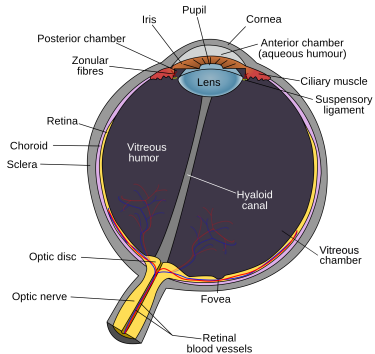


Fig.: The human eye

Eye Movements

There are four main eye movements:

- *saccade*
rapid change of the visual center
- **fixation**
visual tracking of a stationary object
- *smooth pursuit*
visual tracking of a moving object
- *nystagmus*
compensation of retinal movement

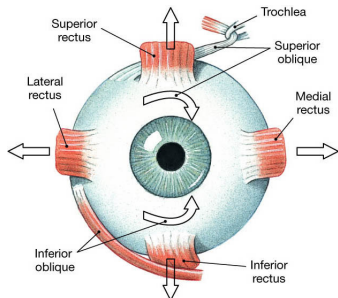


Fig.: Eye Muscles

Camera-Based Eye Tracking

Basic principle:

Gaze tracking by detecting features of the eye e. g. corneal reflections. In this case an infrared diode emits IR light that is reflected at several layers of the eye. Each reflection is a function of the position of the eye and is recorded with a camera.

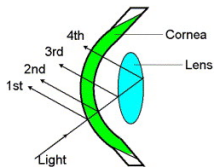


Fig.: The four Purkinje images

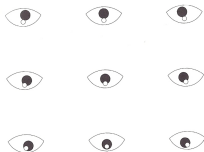


Fig.: Positions of the first Purkinje image

Experimental Setup - Theory

Pattern Recognition Pipeline

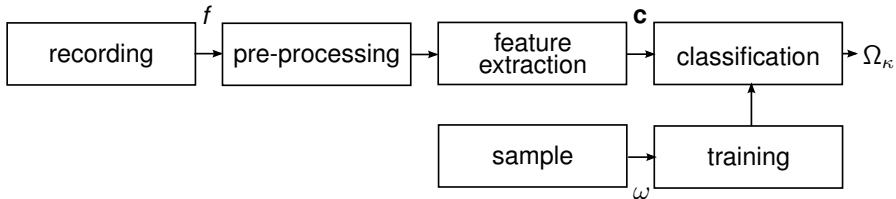


Fig.: The pipeline of pattern recognition by Niemann

Data Recording

For the data recording a binocular infrared eye tracker based on the principle of corneal reflection was used.

It recorded:

- position of the eye at a given time (waypoint)
- fixation and saccades
- pupil size at each waypoint



Fig.: Binocular eye tracker

Pre-processing

Done by both the eye tracker and the “Eye Tracking Tool”

- Eye tracker assigns gaze direction, pupil size and time and exports the data.
- The “Eye Tracking Tool” reads the data and can apply the following steps.

Pre-processing (cont.)

Region of Interest (ROI)

- elliptical or polygonal shaped
- defined by the user in the "Eye Tracking Tool"
- 2 sets of ROI used for evaluation

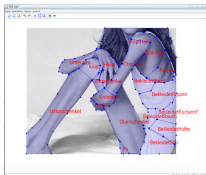


Fig.: Body part ROI set

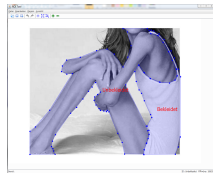
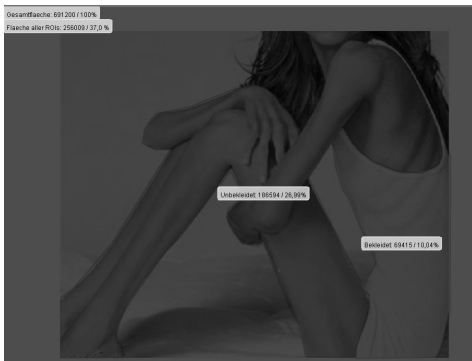


Fig.: clothed-unclothed ROI set

Pre-processing (cont.)

Area of ROIs

Calculation of the area of the ROIs



Pre-processing (cont.)

Fixation in ROIs

Calculation of the fixation time in a single ROI



Feature Extraction

Extracted Features were:

- **Relative time per area (RTPA)**
Fixation time in a ROI divided by its area
- **Region of interest switch (ROI switch)**
Number of fixation changes between ROIs
- **Pupil size**
Maximal pupil size within each ROI

Principal Component Analysis

General Concept:

- reduce the dimensionality of the data, which consists of a large number of interrelated features.
- keep the variation and the information.
- Reform the data into new uncorrelated variables, the *principal components*.

The variance covered (VC) value (0–100 %) describes the covered variance of the features and is later used to adjust the reduction of the data.

Classification

The classification is done with the WEKA data mining software.
As classifier an *attribute selected classifier* was used. This reduces the test and training data with attribute selection before the data gets classified.

- Principal component analysis
- Ranker search
- Naïve Bayes classifier

Training:

The training is done with a *leave-one-out cross-validation*.

Experimental Setup - Application



Fig.: Eye tracking in progress

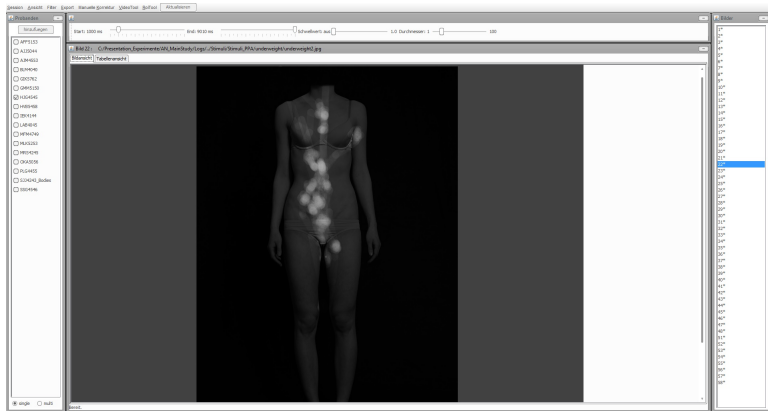


Fig.: Eye Tracking Tool

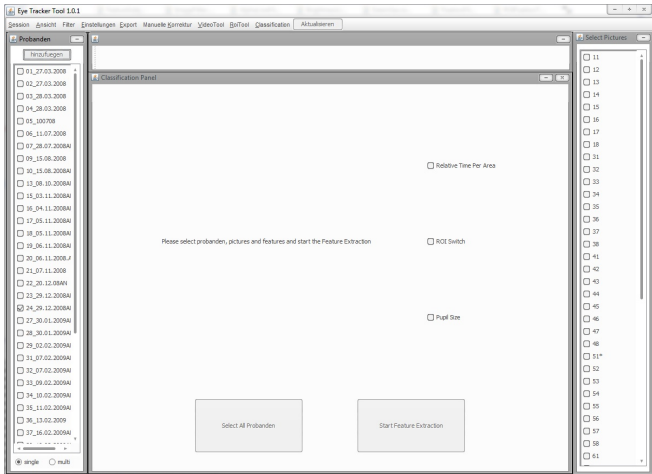


Fig.: Eye Tracking Tool classification menu

Evaluation Process

- For each feature combination (7 different) and each of the two ROI sets one feature extraction was done with the “Eye Tracking Tool”.
- This resulted in a total of 14 .arff files ($7 \cdot 2$)
- Each file was then classified with different VC values in the PCA (5-100%).
- For the best VC-value of each file the ROC-curve and the AUC were calculated.
- These values were compared.

Feature Combination	RTPA	ROI Switch	Pupil Size
1	x		
2		x	
3			x
4	x	x	
5	x		x
6		x	x
7	x	x	x

Tab.: The different combination of feature sets tested.

Results

Results

- Results of the clothed-unclothed ROI set
- Results of the body part ROI set
- Comparison with the results from Horndasch et al.

Results of the Clothed-Unclothed ROI Set

- RTPA feature performs well.
- Pupil size and ROI switch feature have a bad performance.
- Best combination is RTPA and ROI switch, but with decreased accuracy.

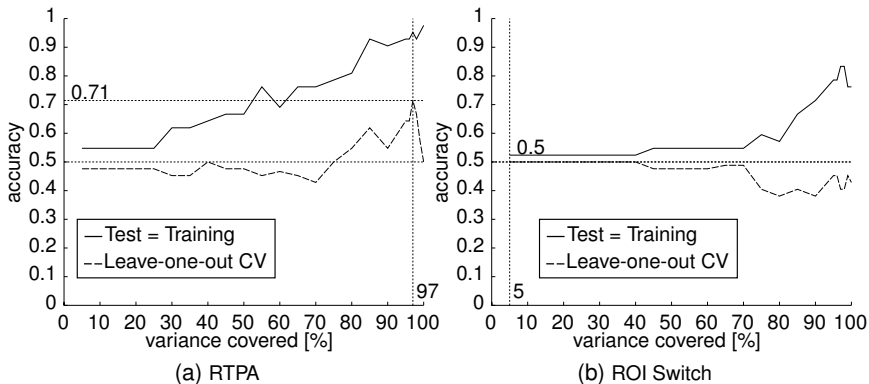
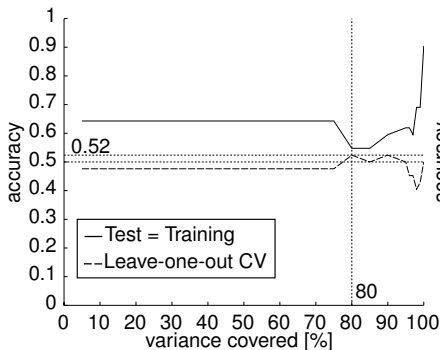
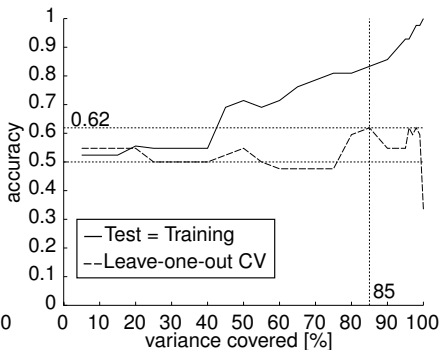


Fig.: Graphs showing the maximal accuracy and VC values of the clothed-unclothed ROI set.



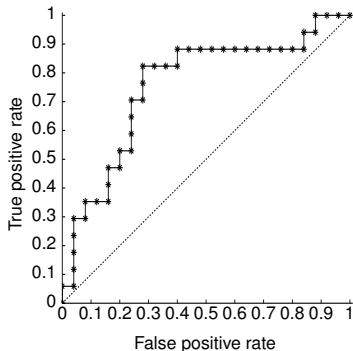
(a) Pupil Size



(b) RTPA & ROI Switch Combination

Fig.: Graphs showing the maximal accuracy and VC values of the clothed-unclothed ROI set.

Results of the Clothed-Unclothed ROI Set (cont.)



		True class	
		patient	control
Classification result	control	14	3
	patient	9	16

AUC = 0.76

accuracy = 0.71

max VC = 97%

Fig.: ROC-curve of the RTPA feature.

Results for the Body Part ROI Set

Similar results as in the clothed-unclothed ROI set

- RTPA feature shows good results.
- Again both pupil size and ROI switch were performing bad.
- Best combination is RTPA and ROI switch, this time with increased accuracy.

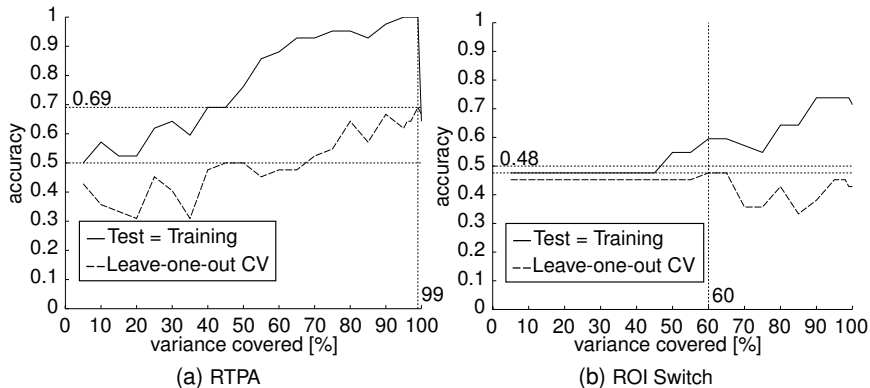
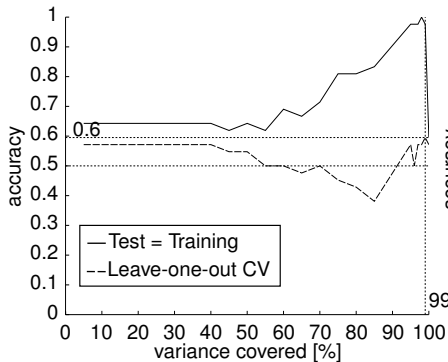
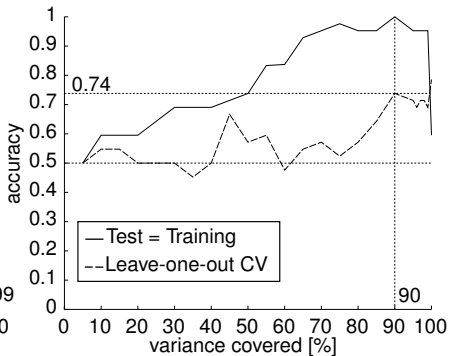


Fig.: Graphs showing the maximal accuracy and VC values of the body part ROI set.



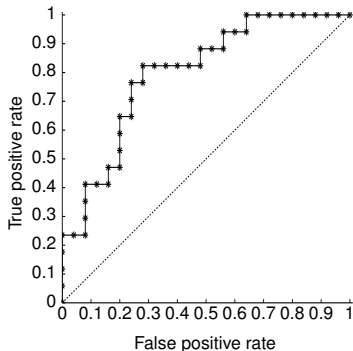
(a) Pupil Size



(b) RTPA & ROI Switch Combination

Fig.: Graphs showing the maximal accuracy and VC values of the body part ROI set.

Results for the Body Part ROI Set (cont.)



		True class	
		patient	control
Classification result	control	12	5
	patient	6	19

AUC = 0.85

accuracy = 0.74

max VC = 90%

Fig.: ROC-curve of the RTPA and ROI switch combination

Comparison with the results from Horndasch et al.

Results of Horndasch et al.

- “Index body parts” didn’t draw visual attention of eating-disordered patients to a greater extend then that of normal controls.
- Eating-disordered girls spent significantly more time than healthy controls looking at unclothed body parts.

Outcome of PCA shows selected features are often “index body parts”.

According to the study the results of the clothed-unclothed ROI set should be better.

Conclusion

Conclusion

- In this thesis it was shown that eye tracking data classification is possible.
- Maybe there are other features which can yield to even better results (higher than 0.74 accuracy).
- Test with higher number of subjects would be preferable (more than 42).

Thank you for your attention!

Questions, wishes, suggestions?

The End