Recognition of Curiosity Using Eye Movement Analysis

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Abstract
Among the different personality traits that guide our behaviour, curiosity is particularly interesting for context-aware assistive systems as it is closely linked to our well-being and the way we learn. This work proposes eye movement analysis for automatic recognition of different levels of curiosity. We present a 26-participant gaze dataset recorded during a real-world shopping task with empirically validated curiosity questionnaires as ground truth. Using a support vector machine classifier and a leave-one-person-out evaluation scheme we can discriminate between two to four classes of standard curiosity scales well above chance. These results are promising and point towards a new class of context-aware systems that take the user's curiosity into account, thereby enabling new types of interaction and user adaptation.

ACM Classification Keywords
H.1.2 [Models and Principles: User/Machine Systems]: Human information processing; I.5.2 [Pattern Recognition: Design Methodology]: Pattern analysis

Introduction
Eye movements were previously used in context-aware computing for tasks such as activity recognition [4, 14] or the assessment of covert aspects of user state that are difficult or even impossible to deduce using other sensing

Figure 1: Eye Tracking Glasses from SensorMotoric Instruments that are connected to an Android Phone for unobtrusive recording (top) and a sample scene image from one of the recordings (bottom). The red dot highlights the point of gaze.

modalities, e.g. visual memory recall [2]. Personality is another cover aspect of user state and is known to be hard to infer from other modalities [10] and to be linked to eye movements [9, 11]. Curiosity is a key personality trait for motivating visual inspection of the environment [6], can predict eye movement characteristics in scene-viewing [12] and might correlate with a person's distress tolerance, risk of anxiety and more holistic personality tests [8]. Hence, predicting curiosity has considerable potential for context-aware computing and may lead to a new class of systems for user adaptation and mental health monitoring based on personality information.

As a first step towards this vision, we investigate eye movement analysis as a means to automatically recognise curiosity. We evaluated gaze data from 26 participants performing a real-life shopping task. This setting was chosen as shopping was previously used in studies on eye movements during decision making [7], although the effect of a stable trait such as curiosity should be detectable regardless of the current activity. Ground truth was established by common questionnaires [8, 6]. We propose a set of eye movement features and a method for supervised recognition of personality traits, with which we can recognise three classes of perceptual curiosity with an average F1-score of about 50%.

Study

While previous works examined curiosity only under constraint laboratory conditions, we designed a user study to examine whether curiosity can be predicted based on natural eye movements during a real-world task.

Participants and Apparatus

26 students and staff of our university participated in the data collection (21 female, aged 18 to 41 years) and were paid A$15 as compensation. We used a state-of-the-art head-mounted eye tracker, the Eye Tracking Glasses (ETG) from SensorMotoric Instruments, which records binocular gaze data at 60 Hz and a high-resolution scene video via an Android phone (see Figure 1).

Procedure

After an introduction, the eye tracker was calibrated and participants were given A$5 to go to one of the shops on campus and buy an item of their choice which they were allowed to keep or eat. The recording also included navigation to and from the shop as well as social interaction with staff. All participants were instructed to behave normally but avoid direct sunlight and minimise social interactions on the way. In total, about one third of the data was recorded inside a shop, two thirds outside. After 10 to 15 minutes, the participants returned to the lab and filled in two curiosity questionnaires: the Curiosity and Exploration Inventory (CEI) [8] and the Perceptual Curiosity Scale (PCS) [6]. Both scales comprise two subscales each: $\mathrm{CEI\text{-}E}$ and $\mathrm{CEI\text{-}S}$ refer to the embracing and stretching subscales; $\mathrm{PCS\text{-}S}$ and $\mathrm{PCS\text{-}D}$ stand for specific and diversive exploratory behaviour. The subscales measure slightly different aspects of curiosity, such as a strive towards or full engagement in new experiences [1].

Recognition of Curiosity

We discretised the curiosity questionnaire scores into two, three, and four classes. The class boundaries were determined equidistantly between minimum and maximum scores in our dataset: class boundary b_i was computed as $b_i = i \cdot \frac{y_{\max} - y_{\min}}{n_c} + y_{\min}$, where $y_{\max}$ and $y_{\min}$ are the minimum and maximum scores our participants reached and n_c is the number of classes. The histogram of all ground truth curiosity scores in our dataset and exemplary class boundaries are shown in Figure 2.

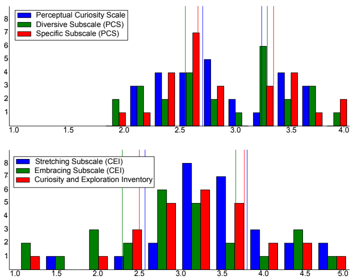

Figure 2: Histograms of the curiosity scores our participants reached on both scales and their subscales. Vertical lines visualise the class boundaries we chose.

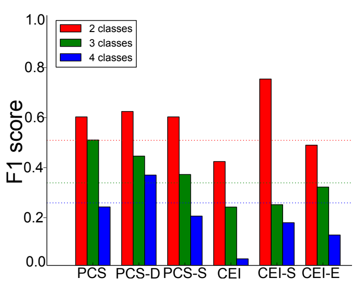

Figure 3: F1 Scores for all curiosity scales and class problems in comparison to chance level (dashed lines).

The gaze data was processed as suggested by Bulling et al. for general eye-based activity recognition [3]: Fixations were detected based on dispersion [13] and all movements in between were defined to be saccades. From fixations, saccades, and information on blinks and pupil diameter provided by the eye tracker software we extracted 56 features (see Table 1) using a sliding window approach with a window size of 15 sec and a step size of 7.5 sec. The window size was chosen to resemble the stimulus presentation time in a previous laboratory experiment [12]. Despite our real-world setting, no de-noising was applied.

Separate support vector machines (SVM) for each curiosity (sub)scale and number of classes were trained using radial basis function kernels and identical standard parameters [5]. The curiosity was predicted by the median of all predictions based on single time windows.

Results

To evaluate the SVM for each trait and number of classes (2, 3 or 4), we used a leave-one-out scheme: For each participant, a prediction was derived from an SVM trained on all other participants. All predictions were compared to the ground truth questionnaire scores based on the F1 score (harmonic mean of precision and recall). Figure 3 shows the F1 scores and chance level, i.e. the best achievable performance by either randomly choosing any class or always the most frequent one.

Participants could be classified above chance as one of up to three classes on the PCS and $\mathrm{PCS\text{-}S}$. On the $\mathrm{PCS\text{-}D}$, even four classes can be distinguished above chance level. From the CEI scales, only two classes of $\mathrm{CEI\text{-}S}$ can be inferred above chance level.

A more detailed plot of the individual classification results for the best scale in our evaluation ($\mathrm{PCS\text{-}D}$) is provided in Figure 4. For each participant, the figure shows the true value before discretisation as well as the SVM prediction. For 11 of the 26 participants, the correct class is predicted. Many misclassifications occurred for participants close to the class boundaries.

Fixation (8)	rate, mean, max, var of durations mean/var of mean/var POG within one fix.
Saccades (12)	rate/ratio of (small/large/right/left) sacc. mean, max, variance of amplitudes
Combined (1)	ratio saccades to fixations
Wordbooks (24)	number of non-zero entries maximum and minimum entries as well as their difference for n-grams with $n \leq 4$
Blinks (3)	rate, mean/var blink duration
Pupil Diameter (8)	mean/variance of mean/variance during saccades/fixations

Table 1: The 56 features used for recognition of curiosity. The number of features per category is given in parentheses.

Discussion

Classification results for up to 4 classes on PCS scales above chance for unseen participants might suggest that perceptual curiosity influences gaze behaviour in a similar way across people. The error on CEI scales is higher, maybe because they comprise other aspects of curiosity that might be less straight forward in their effect on gaze.

Multiple character traits often correlate with each other, so multi-target methods considering further traits could potentially explain more variance in the data than the single target classification studied here.

Being able to sense a user's personality might improve systems in several ways: the user's attention could be guided to details that would be otherwise missed if the user does not have a strong strive for exploration. Health

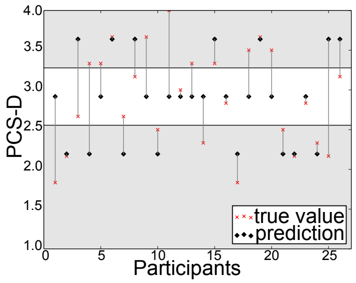

Figure 4: Detailed classification result for 3 classes of the Diversive Subscale of Perceptual Curiosity.

monitoring applications could benefit from considering curiosity, e.g. in the case of anxiety disorders. Moreover, E-learning systems could benefit from personalised content presentation based on the user's personality [10].

Conclusion

In this work we presented a method to predict different levels of curiosity from eye movements based on a dataset of 26 people involved in a shopping task. While previous work in experimental psychology has demonstrated the significant influence of curiosity on gaze behaviour in controlled settings, this work is the first to show that real-world visual behaviour contains sufficient information to automatically predict different levels of curiosity for unseen people. These results are promising and open up new avenues for research on context-aware systems that sense and adapt to different personality traits of the user, including but potentially also beyond curiosity.

References

[1] Berlyne, D. E. *Conflict, arousal, and curiosity.* McGraw-Hill Book Company, 1960.

[2] Bulling, A., and Roggen, D. Recognition of visual memory recall processes using eye movement analysis. In *Proc. UbiComp* (2011), 455–464.

[3] Bulling, A., Ward, J. A., Gellersen, H., and Tröster, G. Eye movement analysis for activity recognition using electrooculography. *IEEE TPAMI 33*, 4 (2011), 741–753.

[4] Bulling, A., Weichel, C., and Gellersen, H. EyeContext: Recognition of High-level Contextual Cues from Human Visual Behaviour. In *Proc. CHI* (2013), 305–308.

[5] Chang, C.-C., and Lin, C.-J. LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology 2* (2011), 27:1–27:27.

[6] Collins, R. P., Litman, J. A., and Spielberger, C. D. The measurement of perceptual curiosity. *Personality and Individual Differences 36*, 5 (2004), 1127–1141.

[7] Gidlöf, K., Wallin, A., Dewhurst, R., and Holmqvist, K. Using eye tracking to trace a cognitive process: Gaze behaviour during decision making in a natural environment. *JEMR 6*, 1 (2013), 1–14.

[8] Kashdan, T. B., Gallagher, M. W., Silvia, P. J., Winterstein, B. P., Breen, W. E., Terhar, D., and Steger, M. F. The curiosity and exploration inventory-ii: Development, factor structure, and psychometrics. *Journal of Research in Personality 43*, 6 (2009), 987–998.

[9] Kaspar, K., and König, P. Emotions and personality traits as high-level factors in visual attention: a review. *Frontiers in Human Neuroscience 6*, 321 (2012).

[10] Kaya, H., and Salah, A. A. Continuous mapping of personality traits: A novel challenge and failure conditions. In *Proc. MAPTRAIT Workshop*, ACM (2014), 17–24.

[11] Rauthmann, J. F., Seubert, C. T., Sachse, P., and Furtner, M. R. Eyes as windows to the soul: Gazing behavior is related to personality. *Journal of Research in Personality 46*, 2 (2012), 147 – 156.

[12] Risko, E. F., Anderson, N. C., Lanthier, S., and Kingstone, A. Curious eyes: Individual differences in personality predict eye movement behavior in scene-viewing. *Cognition 122*, 1 (2012), 86 – 90.

[13] Salvucci, D. D., and Goldberg, J. H. Identifying fixations and saccades in eye-tracking protocols. In *Proc. ETRA* (2000), 71–78.

[14] Steil, J., and Bulling, A. Discovery of everyday human activities from long-term visual behaviour using topic models. In *Proc. UbiComp* (2015).