PrivacEye: Privacy-Preserving First-Person Vision Using Image Features and Eye Movement Analysis

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ABSTRACT
As first-person cameras in head-mounted displays become increasingly prevalent, so does the problem of infringing user and bystander privacy. To address this challenge, we present PrivacEye, a proof-of-concept system that detects privacy-sensitive everyday situations and automatically enables and disables the first-person camera using a mechanical shutter. To close the shutter, PrivacEye detects sensitive situations from first-person camera videos using an end-to-end deep-learning model. To open the shutter without visual input, PrivacEye uses a separate, smaller eye camera to detect changes in users’ eye movements to gauge changes in the “privacy level” of the current situation. We evaluate PrivacEye on a dataset of first-person videos recorded in the daily life of 17 participants that they annotated with privacy sensitivity levels. We discuss the strengths and weaknesses of our proof-of-concept system based on a quantitative technical evaluation as well as qualitative insights from semi-structured interviews.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords
Egocentric Vision; Eye Tracking; Gaze Behaviour

INTRODUCTION
Head-mounted devices with built-in first-person cameras, such as action cameras or “smart glasses”, are pushing to the market. These devices do not only allow users to create high-quality, first-person visual imagery but might also enable promising functionalities, such as visual tracking for indoor navigation [30], memory augmentation [17], or character recognition for in-situ translation [32]. However, there are many everyday situations in which first-person cameras pose a privacy risk given that the recorded imagery may contain highly sensitive personal information, such as login credentials, banking information or personal text messages. In addition, images potentially allow to identify depicted persons and may thus also infringe the privacy of bystanders. Particularly in certain locations or during privacy-sensitive tasks, such as personal conversations [23], first-person cameras are therefore often perceived as unpleasant or even undesired [20].

However, despite the significant privacy risks that first-person cameras pose, solutions addressing these challenges are surprisingly limited. Users can employ self-censorship [22] but they are prone to misinterpret situations, be unaware of social norms and legal regulations, or forget to de-activate or re-activate the camera. This might reduce their user experience and comfort, or increase their mental and emotional load – and potentially capture and leak sensitive personal information. Prior work therefore investigated alternative solutions, such as to communicate bystander’s privacy preferences using short-range wireless radio [1], visual markers [41] or techniques to compromise recordings [16, 47]. However, all of these methods require bystanders to take action themselves to protect their privacy. We are not aware of a single work that addressed the problem at the source, i.e. the sensor of the camera itself, as well as the privacy of both the wearer and, by his choice of privacy sensitivity, also of bystanders.

We propose PrivacEye, a proof-of-concept first-person vision system that combines a deep-learning computer vision method to detect privacy-sensitive situations with eye movement analysis to detect changes in the “privacy level” of the current situation. If a privacy-sensitive situation is detected, the scene camera is occluded by a shutter. In contrast to the state of the art, we de-activate the camera completely, thereby...
also signalling this to bystanders. This approach is fully secure but the lack of visual input requires another approach to open the shutter and restart the recording. We propose to use a second camera mounted close to the user’s eye to detect changes in eye movement behaviour. Prior work demonstrated that eye movement analysis can be used to infer visual and physical activities [6, 44], or to detect social interactions and users’ current environment [7]. It is therefore conceivable that eye movements are also related to privacy-relevant situations and activities. Unlike other sensing techniques, such as microphones or infra-red cameras, this approach also does not infringe on the privacy of potential bystanders.

The contributions of this work are three-fold: First, we present PrivacEye, a proof-of-concept system that combines computer vision with eye movement analysis to enable context-specific, privacy-preserving de-activation and re-activation of a first-person camera. Second, we evaluate our system on a dataset of real-world mobile interactions as well as eye movement data annotated with the location, activities, and privacy sensitivity levels of 17 participants. Third, we provide qualitative insights on perceived social acceptability, perceived trustworthiness, and desirability from semi-structured interviews.

RELATED WORK
Our work is related to previous works studying (1) privacy concerns with first-person cameras and (2) methods to enhance the privacy of such cameras.

Privacy concerns with first-person cameras
First-person (egocentric) cameras see ever more widespread adoption in action cameras or as part of head-mounted displays and smart glasses. First-person cameras are better suited for continuous and unobtrusive video recordings than phone-integrated cameras and, in contrast to CCTVs, mobile and controlled by individuals. This makes them to be perceived more unsettling by bystanders [11]. Both users’ and bystanders’ privacy concerns and attitudes towards head-mounted devices with integrated cameras were found to be affected by context, situation, usage intentions [23], as well as user group [39]. Hoyle et al. showed that the presence and number of people in a picture, of specific objects (e.g., computer displays, ATM cards, physical documents), as well as location and activity affected whether lifeloggers deemed an image “shareable” [20]. They also highlighted the need for automatic privacy-preserving mechanisms detecting those elements, as individual sharing decisions are likely to be context-dependent and subjective. Their results were partly confirmed by Price et al. who, however, found no significant differences in sharing when a screen was present [38]. Chowdhury et al. [10] found that whether lifelogging imagery is suitable for sharing is (in addition to content, scenario, and location) mainly determined by its sensitivity. Ferdous et al. proposed a set of guidelines that, amongst others, include semi-automatic procedures to determine the sensitivity of captured images according to user-provided preferences [14]. All of these works underline the highly privacy-sensitive nature of head-mounted displays, and first-person cameras in particular, as well as the importance of active measures to protect the privacy of users and bystanders.

Enhancing the privacy of first-person cameras
Works in the area of enhancing the privacy of first-person cameras can be clustered according to whether they focused on potential bystanders or the user himself. To increase privacy for bystanders, researchers suggested communicating their privacy preferences to nearby capture devices using wireless connections as well as mobile or wearable interfaces [26]. Others suggested to prevent non-compliant capturing devices from unauthorised recording by compromising the recorded imagery, e.g., using infra-red light signals [15, 50] or by disturbing face recognition [16]. In contrast to our approach, these techniques all require the bystander to take action, which might be impractical due to costs and efforts [11].

Work on increasing the privacy of the user has mainly focused on techniques that require active involvement of the user. For example, Templeman et al. introduced PlaceAvoider, a technique that allowed users to “blacklist” sensitive spaces, e.g., bathrooms or bedrooms, performing image analysis with object-level and scene-level image features to classify where a photo was taken [46]. A similar approach was followed by Erickson et al. who introduced a method to identify security risks, such as ATM, keyboards, and credit cards, in images captured by first-person wearable devices [13]. However, instead of assessing the whole scene in terms of privacy sensitivity, their system only detected individual sensitive objects. Raval et al. presented MarkIt, a computer vision based privacy marker framework that allowed users to use self-defined bounding boxes and hand-gestures to restrict visibility of content on two dimensional surfaces (e.g., white boards) or sensitive real-world objects [40]. Similarly, ScreenAvoider allowed users to control the disclosure of images with computer screens and their sensitive content detected using a Convolutional Neuronal Network (CNN) [24, 25].

While all of these methods improved privacy, they either only did so post-hoc, i.e. after images had already been captured, or they required active user input. In contrast, our approach aims to prevent potentially sensitive imagery to be recorded at all and automatically in the background, i.e. without engaging the user. Unlike current computer vision based approaches that work in image space, e.g. by masking objects or faces [40, 43, 50], restricting access [24] or deleting recorded images post-hoc [46], we (1) de-activate the camera completely using a mechanical shutter and also signal this to bystanders. Our approach further employs, for the first time, eye movement analysis for camera re-activation which unlike other sensing techniques (e.g., microphones, infra-red cameras), does not compromise the privacy of potential bystanders.

DESIGN RATIONALE AND INTERACTION DESIGN
We first discuss the rationale behind PrivacEye and motivate our design decisions based on user and bystander goals.

Goals and Expectations of Users & Bystanders
To illustrate the goals and expectations of users and bystanders of smart glasses and the requirements that result there from, we use a fictive scenario with two main characters, Ada (a user of smart glasses), and Ben (an acquaintance of hers) who assumes the bystander role. Ada uses a smart glasses with
Examples uninteresting (e.g., flooring), blurry, or over-/underexposed imagery incidental (e.g., bystanders) or inadvertent (e.g., login screens) captures lifestyle shots, (live-) video (e.g., for lifelogging, social media), continuous camera stream (e.g., for tracking, localisation) secret photography (e.g., upskirts), or documentation purposes (e.g., accidents) incidental (e.g., bystanders) or inadvertent (e.g., login screens) captures of sensitive content

Goal: Avoid Misclosure of Sensitive Data

The reason why Ada is wearing the smart glasses device is that she wants to make use of a particular functionality, in her case: visual navigation. However, due to their “always-on”, characteristic, her glasses do not only capture what is intended to be captured. Regarding the sensitivity of their content, and recording intention, the captured imagery can be classified in a 2 × 2 matrix as depicted in Figure 2a. The navigation aid is based on capturing of the landmarks required for tracking and localisation (intended, non-sensitive imagery). In addition also unintended imagery is captured. These images can be either just uninteresting or useless (unintended, non-sensitive) or contain sensitive data (unintended, sensitive) (c.f., [19, 24]). For illustration, we list examples in Table 2b. To prevent misclosures [8], sensitive data should not be captured. However, requiring the user to constantly monitor her actions and environment for potential sensitive information (and then deactivate the camera manually) might increase workload and cause stress. While her mind is occupied elsewhere during her travels, she might be forgetful, overlook sensitive items or misinterpret certain situations. Thus, we assume that automatic support from the system would be desirable for her.

Goal: Avoid Social Friction

The system also reacts to interpersonal conversations. So, when Ben approaches Ada in a café and they start to chat, it grants them privacy by de-activating the camera, which Ben can also infer from the closed shutter. While the first-person camera is de-activated, the system observes Ada’s eye movements. When Ben leaves, or Ada puts her documents away and resumes another activity, e.g., sightseeing, the system detects a change in eye behaviour, and re-activates the first-person camera, without her having to think of it.

The smart glasses recording capabilities would cause social friction between Ada and Ben, if there was no clear indication whether the camera is on or off. If the recording status is unclear, bystanders might even perceive device usage as a privacy threat if the camera is turned off [23]. In consequence they feel uncomfortable around those devices [4, 11, 12, 23]. In addition, automatic re-activation ensures that Ada does not forget to enable the camera manually, when leaving the café. While for visual navigation, her forgetfulness might only impact localisation performance, for a lifelogging use case it might lead to “lost memories” and disappointment.

Design Requirements

The interaction design of PrivacEye addresses three design requirements, following the previously discussed scenarios, and resulting from an analysis of prior research:

Requirement 1: The user can make use of the camera-based functionality without the risk of misclosures or leakage of sensitive information.

Requirement 2: The system pro-actively reacts to presence or absence potentially privacy-sensitive situations and objects.

Requirement 3: The camera device communicates the recording status clearly to both user and bystander.

PrivacEye PROTOTYPE

With PrivacEye we present a proof-of-concept prototype that aims to address all of these requirements. The hardware proto-
Type, shown in Figure 3, is based on the PUPIL head-mounted eye tracker [21] and features one 640 × 480 pixels camera (“eye camera”) recording the right eye from close proximity (30 fps), and a second camera (1280 × 720 pixels, 24 fps) recording the user’s environment (“scene camera”). The first-person camera is equipped with a fish eye lens with a 175° field of view and can be closed with a custom-made mechanical shutter. The cameras and shutter were connected to a laptop via USB. Privaceye further consists of two main software components: 1) detection of privacy-sensitive situations to close the mechanical camera shutter and 2) detection of changes in users’ eye movements that are likely to indicate suitable points in time for re-opening the camera shutter.

Detection of Privacy-Sensitive Situations
To detect privacy-sensitive situations, inspired by prior work on predicting privacy-sensitive pictures posted in social networks [33], we used a pre-trained Googlenet, a 22-layer deep convolutional neural network [45]. We adapted the original Googlenet model for our specific prediction task by adding two additional fully connected (FC) layers. The first layer was used to reduce the feature dimensionality from 1024 to 68 and the second one, a Softmax layer, to calculate the prediction scores. Output of our model was a score for each first-person image indicating whether the situation visible in that image is privacy-sensitive or not. The cross-entropy loss was used to train the model. The model is shown in Figure 4.

Detection of Changes in Eye Movement
A naive, vision-only system could re-open the shutter at regular intervals, e.g. every 30 seconds, to detect whether the current situation is still privacy-sensitive. This approach, however, might negatively affect perceived reliability, and thus increase mistrust in the system, or cause unnecessary distraction, e.g., during conversations. The goal of this second component is to instead detect changes in users’ eye movements that are likely to be linked to changes in the privacy sensitivity of the current situation, and thereby to reduce the number of shutter re-openings as much as possible. To detect such changes we perform two steps: 1) eye movement feature extraction and selection, and 2) change point detection followed by extrema detection using these features.

Feature Extraction and Selection
We extracted characteristic eye movement features using only the eye camera video data. Table 1 summarises the features we extracted from fixations, saccades, blinks, pupil diameter and user’s scan paths, where each saccadic movement is encoded as a character forming words of length n (wordbook). Similar to [5, 18], we extracted these features on a sliding window of 30 seconds (step size of 5 seconds). We then selected the 10 most relevant eye movement features using minimum redundancy maximum relevance (mRMR) feature selection [34].

Change Point Detection
In a second step, we used a state-of-the-art unsupervised method to detect change points in the eye movement time series data [28]. In a nutshell, this statistical method is based
on the non-parametric divergence estimation between time-series samples from two retrospective segments. It uses the relative Pearson divergence as a measure, and is accurately and efficiently estimated by a method of direct density-ratio estimation. Instead of raw eye movement data we directly used the time-series of multi-dimensional eye movement features as input. We set the method’s main parameters $\alpha = 0.01$, $k = 1$, so that every features sample is treated as single input an no additional normalisation is performed, and $n = 20$ to compare the current probability density of the input data with a time point sufficient back in time to detect changes.

Figure 5 shows a sample change detection for one of our participants. The black line is the privacy sensitivity level as annotated by the participant herself. The red dots indicate detected change points. For the change point detection we regard the extrema of the score stream as potential candidates to re-open the camera shutter. Therefore, we use Persistence1D [48] for extracting and filtering minima and maxima of our 1D change score stream. We can steer the number of change points dramatically with the extrema threshold parameter of Persistence1D. When deciding whether a change point detection was correct (green dots) or not (red dots), we allowed for a certain temporal deviation (margin) of the detections from the ground truth changes, which we evaluated in detail. The grey vertical blocks indicate this temporal deviation at the points in time where the ground truth changes from “privacy-sensitive” to “non-sensitive”. Therefore, we investigate the effect of the extrema threshold parameter, as well as the margin parameter to detect change point candidates located in close distance to the ground truth event.

EXPERIMENTS
We evaluated both software components of PrivacEye separately as well as their interplay.

Table 2: Annotation scheme used by the participants to annotate their recordings.

For our evaluations we used a dataset that had been recorded in the context of another project\(^1\) and that we fully annotated with privacy sensitivity ratings (see below).

That dataset was deemed suitable also for the current work given that it contains more than 70 hours of data, continuously recorded from 20 participants over more than four hours each. During the recordings, participants roamed a university campus and performed their everyday activities like meeting people, eating, or working as they normally would during a day at the university. They were further engaged in regular interactions with a mobile phone and were also encouraged to use their own laptop, desktop computer, or music player if desired. The dataset thus covers a rich set of representative real-world situations including sensitive environments and tasks (see Figure 6). The data collection was performed with the same equipment as shown in Figure 3 but without the camera shutter.

Data Annotation
For data annotation we re-invited the original participants to the lab and asked them to annotate their own videos with continuous annotations of location, activity, scene content, and subjective privacy sensitivity level. They again gave informed consent and completed a questionnaire on demographics, social media experience and sharing behavior (based on Hoyle et al. [20]), general privacy attitudes, as well as other-contingent privacy [3] and respect for bystander privacy [38]. General privacy attitudes were assessed using the Privacy Attitudes Questionnaire (PAQ), a modified Westin Scale [49] as used previously by [8, 38].

Annotations were performed using Advene [2]. Participants were asked to annotate continuous video segments showing the same situation, environment, or activity. They could also introduce new segments in case a privacy-relevant feature of the scene changed, e.g., when a participant switched to a sensitive

\( ^{1}\)URL removed for blind review
app on the mobile phone. Participants were asked to annotate each of these segments according to the annotation scheme shown in Table 2, specifically scene content (Q1-7) and privacy sensitivity ratings (Q8). Privacy sensitivity was rated on a 7-point Likert scale ranging from 1 (fully inappropriate) to 7 (fully appropriate). As we expected our participants to have difficulties to understand the concept of “privacy sensitivity”, we rephrased it for the annotation to “How appropriate is it that a camera is in the scene?”. Figure 7 shows the resulting distribution of labelled activities over all participants while Figure 8 visualises the labelled privacy sensitivity levels for each participant. Based on the latter distribution, we pooled ratings of 1 and 2 in the class “privacy-sensitive”, and all others in the class “non-sensitive”. We will use these two classes for all evaluations and discussions that follow.

**Detection of Privacy-Sensitive Situations**

We first evaluated the computer vision component of Privacy-Eye for detecting privacy-sensitive situations. To this end we split the data from each participant into segments. Every time the environment, activity, or the annotated privacy sensitivity level changed a new segment started. We opted for this approach to avoid overfitting and to prevent train and test data from being too similar to each other, which would have simplified the classification task unrealistically. From each segment we extracted one random image that was either used for training or testing our model. To achieve an unbiased training set, we further always selected the number of segments in such a way that during training an equal number of privacy-sensitive and non-sensitive segments was chosen.

We first trained and tested our method using a leave-one-person-out cross validation. That is, we trained on the data of 16 participants and tested on the remaining one – iteratively over all participants and averaging the performance results in the end. Afterwards we trained and tested in a person-specific fashion. In this case we first randomised the order of segments for each participant and then randomly split the data into 70% of the segments for training and 30% for testing. We evaluated the performance using receiver operating characteristic (ROC) and calculated the area under the curve (AUC) – as commonly done for binary classification tasks.

**Person-Independent Evaluation**

Figure 9 shows the ROC curve for person-independent evaluation. The blue line indicates the ROC curve averaged over all participants and the grey band visualises the band corresponding to one standard deviation of the individual results. As we can see, our method performs clearly above chance level (the red dotted line). Using only one image per segment for training we achieve an AUC of 75%.
Afterwards, we evaluated the performance for detecting changes in eye movement behaviour. These changes are correlated with changes in user’s current activity and therefore represents potential candidates to re-open the camera shutter. For the correct detection of change points we allow a margin of up to 60 seconds to count a change point candidate as proposed in [28]. The threshold parameter for the extrema detection is an important parameter to reduce the number of change point candidates. Therefore, we plot in Figure 10 the true positive rate (TPR) and false positive rate (FPR) over all participants for different offsets and extrema threshold (ET) values for the extrema detection. The corrected FPS rate describes the performance in combination with the vision based deep-learning method when checking the first frame after re-opening the camera shutter.

- True positive rate (TPR): $n_{cr}/n_{cp}$,
- False positive rate (FPR): $(n_{al} - n_{cr})/n_{al}$,

where $n_{cr}$ denotes the number of times change points are correctly detected, $n_{cp}$ denotes the number of all change points, and $n_{al}$ is the number of all detected change points. We only consider the change point candidates which are detected during privacy-sensitive situations and outside the detection margin. More specifically, a detected change point at step $t$ is regarded as correct if there exists a true change at step $t^{*}$ such that $t \in \{t^{*} - \text{margin}, t^{*} + \text{margin}\}$. To avoid duplication, we remove the $k_{th}$ change point at step $t_{k}$ if $t_{k} - t_{k-1} < 2 \times \text{margin}$.

Figure 10 shows that the smaller the threshold parameter, the more change point candidates are detected and the higher the true positive rate. Increasing the margin parameter also leads to an increase of the true positive rate and a slowly decrease of the false positive rate. However, the false positive rate is still high. For the reduction of wrong change point candidates we further investigated the interplay of eye movement based change point detection and of the vision-based privacy situation detecting network. For that purpose we tested each first frame after a false positive change point and assumed the camera shutter to re-open and detect whether that frame is privacy-sensitive or not. As you can see from the red curves in Figure 10 this approach is able to reduce the FPR to less than 30%, which means that in the correct detected cases the camera shutter directly closes again.

We finally investigated the feature importance for change detection in eye movements. As described before, we selected the 10 most relevant features for every recording and used these features as input to our change point detection method. Table 4 shows the overall best features as selected by mRMR. We can see that especially the wordbook (WB) features rank highly, as do the saccade and fixation rate features as well as a pupil diameter feature.

Person-Specific Evaluation

Table 3 summarises the results for the person-specific evaluation. As can be seen from the table, the performance increases to more than above 90% AUC for some participants. Upon closer inspection, we noticed that the poorly performing P7, P9, P18, and P19 had only judged few segments as privacy-sensitive and the majority as non-sensitive (cf. Figure 8). Therefore, there was most likely not enough training data available in the person-specific case and, thus, the corresponding AUC scores were close to chance level.

Detection of Changes in Eye Movement Behaviour

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<table>
<thead>
<tr>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P5</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
<th>P11</th>
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<td>0.64</td>
<td>0.78</td>
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Table 3: Area under the curve (AUC) values for each participant as a result of person-specific evaluation for detecting privacy-sensitive situations using the first-person camera.

Figure 9: Received operating characteristic (ROC) curve as a result of leave-one-person-out cross validation for detecting privacy-sensitive situations using the first-person camera.

Figure 10: True positive rate (TPR) and false positive rate (FPR) over all participants for different offsets and extrema threshold (ET) values for the extrema detection. The corrected FPS rate describes the performance in combination with the vision based deep-learning method when checking the first frame after re-opening the camera shutter.
Table 4: Overall top10 features for change detection in eye movement as selected by mRMR.

<table>
<thead>
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<th>Feature</th>
<th>Value</th>
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<tr>
<td>Mean WB2</td>
<td>Saccade rate</td>
</tr>
<tr>
<td>Mean WB1</td>
<td>Mean mean diameter fix</td>
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<tr>
<td>Var WB1</td>
<td>Non zero entries WB3</td>
</tr>
<tr>
<td>Non zero entries WB2</td>
<td>Positive saccade rate</td>
</tr>
<tr>
<td>Diff max-min WB1</td>
<td>Fixation rate</td>
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USER FEEDBACK
Collecting initial subjective feedback during early stages of system development allows us to put research concepts in a broader context and helps to shape hypotheses for future, quantitative user studies. In this section we report on a set of semi-structured one-to-one interviews on smart glasses use in general, and our interaction design and prototype in particular. We recruited 12 (6 females) participants, aged between 21 and 31 years (M=24, SD=3), from the local student population. They were enrolled in overall seven different majors that were highly diverse, ranging from computer science and biology to special needs education. We decided to recruit students given that we believe they and their peers could be potential users of a future implementation of our prototype. However, we acknowledge that our sample, consisting of rather well educated young adults (with six of them having obtained a Bachelor’s degree) is not representative for the general population. Interviews lasted approximately half an hour and participants were reimbursed with a 5 Euro Amazon voucher.

Interview Protocol
During the interview, participants were encouraged to wear and interact with state-of-the-art smart glasses (Vuzix M300 and Sony SmartEyeglass), as well as our prototype. The semi-structured interview was based around the following questions:

Q1 Would you be willing to wear something that would block someone from being able to record you?
Q2 If technically feasible, would you expect the smart glasses themselves, instead of their user, to take care that your privacy is protected automatically?
Q3 Would you feel different about being around someone who is wearing those kinds of intelligent glasses than about those commercially available today? Why?
Q4 If you were using smart glasses, would you be concerned about accidentally recording any sensitive information belonging to you?
Q5 How would you feel about (such) a system automatically taking care that you do not capture any sensitive information?
Q6 How do you think the eye tracking works? What can the system infer from your eye data?
Q7 How would you feel about having your eye movements tracked by your smart glasses?

The questions were designed following a “funnel principle”, with increasing specificity towards the end of the interview. We started with four more general questions (not reported above), such as “Do you think recording with those glasses is similar or different to recording with a cell phone? Why?” based on [11]. This provided the participant with some time to familiarize with the topic, before being presented with the proof-of-concept prototype (use case “bystander privacy”) after Q1 and the use cases “sensitive objects” (e.g., credit card, passport) and “sensitive data” (e.g., login data) after Q4. Eye tracking functionality was demonstrated after Q5. While acquiescence and other forms of interviewer effects cannot be ruled out completely, this step-by-step presentation of the prototype and its scenarios ensured that the participants voiced their own ideas first, before being directed towards discussing concepts included in the actual PrivacEye prototype. Each participant was asked for his/her perspectives on PrivacEye’s concept (Q2-Q5) and eye tracking (Q6 and Q7). The interviews were audio recorded and transcribed for later analysis. Subsequently, qualitative analysis was performed following inductive category development [29]. Key motives and reoccurring themes were extracted and are presented in the following.

Results & Discussion of the User Feedback
In this section we link the interviews back to PrivacEye’s interaction design and discuss implications for future work.

Responsibility
When we designed PrivacEye, we aimed to locate all required sensing and hardware on the user’s side, relieving the bystander of the responsibility to protect his/her privacy. However, similar to the interviewees of Denning et al. [11], the majority of our participants expressed interest in technologies that would allow them to actively block others from recording them (Blocking:yes, n=7). Participants’ comments on the use cases further indicated that they found the “bystander privacy” use case much less convincing than the other two, user-centered, use cases. We attribute this to PrivacEye providing a lack of control from a bystander’s perspective. Nevertheless, for future applications a combination of both technologies, a blocking one on the bystander side, and one similar to PrivacEye, would be more inclusive (e.g., for those without token), or could serve as a fall-back in the case of compatibility issues between smart glasses and blocking devices.

Control
Participants were furthermore encouraged to elaborate on whether the recording status should be user-controlled or system-controlled. P10, who notes “I’d prefer if it was automatic, because if it is not automatic, then the wearer can forget to do that [de-activating the camera]. Or maybe he will say ‘Oh, I do not want to do that’ and then [...] that leads to a conflict. So better is automatic, to avoid questions.”, as well as four other participants preferred the camera to be solely controlled by the system (control:automatic, n=4). They motivate their preference with the user’s forgetfulness and automatisms (n=5), potential non-compliance of users (in the bystander use case, n=1), and increased practicality for the user (n=5): “That would be like a safety net, like for the own forgetfulness. […] one pulls out of one’s bag so unconsciously and types in the PIN one so often ... I think you usually do not know if you have just entered a PIN or not.” (P5)

Only two participants stated to prefer solely (control:manual) control, due to an expected lack of system reliability, and technical feasibility. Two responses were uncodable. All
other participants requested to implement manual confirmation of camera de-activation/re-activation or manual operation as alternative modes (control:mixed, n=4), i.e., they like to feel in control. To meet these user expectations, future interaction designs would have to find an adequate mix of user control and automatic support through the system. E.g., by enabling users to explicitly record sensitive information (e.g., in case of emergency) or label particular, seemingly non-sensitive situations “confidential”.

**Transparency**

Making it transparent (using the 3D-printed shutter) whether the camera was turned on or off was valued by all participants. Seven participants found the integrated shutter to increase perceived safety in contrast to current smart glasses, only few participants stated that they made no difference between the shutter and other visual feedback mechanisms, e.g., LEDs (n=2). Several participants noted that the physical coverage increased trustworthiness, as it made the system more against hackers (concerns:hacking, n=3) than LEDs. Concluding, the usage of physical occlusion could increase perceived safety, and thus could be considered as option for future designs. Participants even noted that the usage of the shutter was similarly reassuring than pasting up a laptop camera (laptop comparison, n=4), which is common practice.

**Trustworthiness**

In contrast, participants also expressed technology scepticism, particularly that the system might secretly record audio (concerns:audio, n=5) or malfunction (concerns:malfunction, n=4). While increasing power of deep neural networks will it make possible to treat malfunctions, system failures or inaccuracies in the future, it will be a challenge for interaction designers to find a cure for this fear of “being invisibly audio-recorded”. A lack of knowledge about eye tracking on both, the user’s and the bystander’s side might even back this misconception. Therefore, future systems using eye tracking for context recognition will have to clearly communicate their modus operandi.

**Perceived Privacy of Eye Tracking**

The majority of participants stated to have no privacy concerns about smart glasses with integrated eye tracking functionality. “I do see no threat to my privacy or the like from tracking my eye movements, this [the eye tracking] would rather be something which could offer a certain comfort.” (P11) Only two participants expressed concerns about their privacy – e.g., due to fearing eye-based emotion recognition (P3); One was uncodeable. This underlines our assumption that eye tracking promises privacy-preserving and socially acceptable sensing in smart glasses, and thus should be further explored.

**DISCUSSION**

In the following we discuss the concept and implementation of PrivacEye based on the technical evaluations and user feedback. We highlight how PrivacEye addresses the aforementioned design and user requirements and substantiate our key findings and conclusions based on related work. In addition, we outline chances for future research arising from the technical limitations of our current proof-of-concept prototype.

**Privacy Preserving Device Behaviour**

*Requirements 1 and 2* demand privacy-preserving device behaviour. With PrivacEye we have presented a computer vision routine that analyses all imagery obtained from the scene camera with regard to privacy sensitivity and – in case the situation deserves protection – reacts by de-activating the scene camera and closing the system’s camera shutter. This approach prevents both, accidental misclosure and malicious procurance (e.g., hacking) of sensitive data, as it has also been positively highlighted by our interview participants.

However, this comes at the cost of having the scene camera unavailable for sensing after it has been de-activated. PrivacEye solves this problem by using a second eye camera that allows us, in contrast to prior work, to locate all required sensing hardware on the user’s side. With PrivacEye we provided a proof-of-concept that context-dependent re-activation of a first-person scene camera is feasible using only eye movement data. Future work will be able to build upon these findings and further explore eye tracking as a sensor for privacy-enhancing technologies. In our current prototype, very short privacy-sensitive situations are difficult to detect, and re-opening of the camera shutter, particularly at the beginning of a recording, requires at least 200 seconds of eye movement data. While it is unlikely that users put on their glasses while being engaged in a privacy-sensitive situation, improving on both of these points is nevertheless desirable and thus an important direction for future work.

**Defining Privacy Sensitivity**

An analysis of related work has shown that the presence of a camera may be perceived appropriate or inappropriate depending on social context, location, or activity [19, 20, 38]. However, related work does, to the best of our knowledge, not provide any insights on eye tracking data in this context. For this reason, we run a dedicated data collection and annotation. Designing a practicable data collection experiment requires to reduce the overall time spent by a participant for data recording and annotation to a reasonable amount. Hence, we made use of an already collected data set, and re-invited the participants only for the annotation task. While the pre-existing data set provided a rich diversity of privacy-sensitive locations and objects, including smart phone interaction, and realistically depicts everyday student life, it is most likely not applicable to other contexts, e.g., industrial work, or medical scenarios. For PrivacEye we rely on a 17 participants large, ground truth annotated dataset with highly realistic training data. Thus, the collected training data cannot be fully generalised, e.g., to other regions or age groups. On the plus side however, this data already demonstrates that in a future real-world application, sensitivity ratings may vary largely between otherwise similar participants. This might be also affected by their (supposedly) highly individual definition of “privacy”. Consequently, a future consumer system should be pre-trained and then adapted on-line, based on personalised retraining after user feedback. In addition, users should be enabled to select their individual “cut-off”, i.e., the level from which on recording is blocked, which was set to “2” for PrivacEye. Real-life users might chose more rigorous or relaxed “cut-off” levels depending on
their personal preference. Initial user feedback also indicated that an interaction design that intertwines automatic, software-controlled de- and re-activation, with conscious control of the camera by the user could be beneficial.

**Utilising Eye Tracking for Privacy-Enhancement**

With regard to bystander privacy eye tracking is advantageous, as it only senses the user respectively his/her eye movements. In contrast to e.g., microphones or infra-red sensing, it does sense bystander and/or environment only indirectly via the user’s eye motion or reflections. Furthermore, eye tracking allows for implicit interaction and is non-invasive, and we expect it to become integrated into commercially available smart glasses in the near future. On the other hand, as noted by Liebling et al. [27] and Preibusch [37] eye tracking data is a scare resource that can tell user attributes such as age, gender, health, and their current task. For this reason, one could hypothesise that the collection and use of the data captured by eye tracking devices might be perceived as potential threat to user privacy. However, our interviews showed that eye tracking was not perceived as problematic by a large majority of our participants. Nevertheless, eye tracking data must be protected by appropriate privacy policies and data hygiene.

**Communicating Privacy Protection**

The interaction design of PrivacEye tackles Requirement 3 using a non-transparent shutter. Ens et al. [12] reported that the majority of their participants expected to feel more comfortable around a wearable camera device if it clearly indicated whether the camera was turned on or off. Hence, our proposed interaction design aims to improve bystander’s awareness of recording status by employing an eye metaphor. For our prototype we opted to implement the “eye lid” as retractable shutter made from non-transparent material: open when the camera is active, closed when the camera is de-active. Thus, the metaphor mimics “being watched” by the camera. This way, it can be ensured that bystanders can comprehend the recording status without prior knowledge, as eye metaphors have been widely employed for interaction design, e.g., to distinguish visibility or information disclosure [31, 36, 42] or to signal user attention [9]. Furthermore, in contrast to visual status indicators, such as point lights (LEDs), physical occlusion is non spoofable (c.f., [11, 35]). This concept has been highly appreciated during our interviews, which is why we would recommend adopting it for future hardware designs.

**CONCLUSION**

In this work we presented PrivacEye, a proof-of-concept system that combines computer vision with eye movement analysis to enable context-specific, privacy-preserving de-activation and re-activation of a first-person camera. To the best of our knowledge, our system is the first of its kind that prevents potentially sensitive imagery to be recorded at all and without the need for active user input. We evaluated PrivacEye both quantitatively and qualitatively by collecting initial, subjective user feedback of 12 potential future users. Our evaluations and interviews demonstrated both the technical feasibility and practical appeal of PrivacEye. We are confident that the rapidly increasing capabilities of today’s deep neural networks will soon allow to push our proof-of-concept prototype towards an effective real-world application enabling privacy-preserving day-to-day usage of “always-on” smart glasses in real-time.

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