The Past, Present, and Future of Gaze-enabled Handheld Mobile Devices: Survey and Lessons Learned

Mohamed Khamis[1,2], **Florian Alt**[1,3,4], **Andreas Bulling**[5]
[1]LMU Munich, Germany
[2]University of Glasgow, Scotland
[3]Munich University of Applied Sciences, Germany
[4]Bundeswehr University Munich, Germany
[5]Max Planck Institute for Informatics, Saarland Informatics Campus, Germany
mohamed.khamis@ifi.lmu.de, florian.alt@ifi.lmu.de, bulling@mpi-inf.mpg.de

ABSTRACT
While first-generation mobile gaze interfaces required special-purpose hardware, recent advances in computational gaze estimation and the availability of sensor-rich and powerful devices is finally fulfilling the promise of pervasive eye tracking and eye-based interaction on off-the-shelf mobile devices. This work provides the first holistic view on the past, present, and future of eye tracking on handheld mobile devices. To this end, we discuss how research developed from building hardware prototypes, to accurate gaze estimation on unmodified smartphones and tablets. We then discuss implications by laying out 1) novel opportunities, including pervasive advertising and conducting in-the-wild eye tracking studies on handhelds, and 2) new challenges that require further research, such as visibility of the user's eyes, lighting conditions, and privacy implications. We discuss how these developments shape MobileHCI research in the future, possibly the next 20 years.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; H.5.2. User Interfaces: Input devices and strategies (e.g., mouse, touchscreen)

Author Keywords
Mobile devices; Gaze Estimation; Gaze Interaction; Smartphones; Tablets; Eye Tracking

INTRODUCTION
Eye tracking and gaze-based interaction on handheld mobile devices have been studied for more than 15 years in Mobile HCI. Recently, advances in visual computing, processing power of said devices, and their front-facing cameras, pave the way for eye tracking to deliver its promises on off-the-shelf handheld mobile devices. In particular, the introduction of high-quality or even depth cameras on commodity devices, such as Google's Project Tango and Apple's iPhone X, will be a turning point, and even more significant than how head-mounted eye tracking is currently transforming mobile gaze recordings [16]. These advances have the potential to take eye tracking on mobile devices from research labs to consumer mobile devices and, thus, to be used by billions of users on a daily basis. This will make pervasive eye tracking on handhelds an "app-installation away", which can in turn have a strong impact on Mobile HCI research.

Despite the mentioned advances and the significant potential this creates both from a research as well as from a commercial perspective, a holistic view of how research on gaze-enabled handheld mobile devices developed in the past decades is missing as of today. With this paper we close this gap.

We identify three major applications areas of eye tracking on handheld mobile devices, namely 1) gaze behavior analysis, 2) implicit gaze interaction, and 3) explicit gaze interaction. We then summarize existing research in these different areas over the last 15 years, and describe latest technical advances that, for the first time, enable full on-device processing. Finally, we make an attempt to look into the future of eye tracking on handheld mobile devices by discussing both the challenges and novel opportunities that these technical advances will bring.

In our review, we cluster the existing work into the "past", where hardware modifications were necessary for gaze-enabled handheld mobile devices, followed by the "present", where eye tracking and eye-based interaction is performed on off-the-shelf devices without any hardware modifications. We studied the lessons learned from each phase, and based on that we discuss the "future" of gaze-enabled handheld mobile devices. By doing so, we uncover novel opportunities: For example, the recent developments allow for conducting field studies of gaze behavior in the wild when, for example, using location-based services, or when perceiving websites and mobile apps while commuting, walking, etc. At the same time, these developments present novel challenges that are beyond hardware limitations of the past. This opens up new frontiers for research: How can mobile devices adapt to different levels of face and eyes visibility which are influenced by holding postures and user's clothing? How can accuracy of

MobileHCI '18, September 3–6, 2018, Barcelona, Spain

ISBN 978-1-4503-5898-9/18/09...$15.00
DOI: https://doi.org/10.1145/3229434.3229452

gaze estimation be maintained with the naturally shaking and mobile environment of handheld devices? How can eye tracking adapt to lighting conditions that vary widely in mobile contexts? What are the implications of pervasive eye tracking on privacy? We discuss these questions among others and propose recommendations and directions for future work.

Contribution Statement
This work makes the following contributions: (1) we present the first holistic view of the past, present and future of eye tracking on handheld mobile devices, and the learned lessons from the former two, (2) we summarize and cluster existing applications of gaze into gaze behavior analysis, implicit and explicit interaction, and (3) we discuss challenges and novel opportunities to guide future MobileHCI research in this area.

GAZE-ENABLED HANDHELD MOBILE DEVICES
Handheld mobile devices can leverage the user's gaze for a multitude of HCI applications. This is demonstrated by the continuously increasing contributions in this area by the research community. As shown in Figure 1, out of the 62 papers related to eye tracking on handheld mobile devices, 44 were published in the last 5 years.

Eye tracking has a lot of potential in understanding users' behavior on handheld mobile devices. Furthermore, it is a capable tool for usability analysis [45]. The unique context of handheld devices has resulted in eye tracking uncovering behaviors that are different compared to those associated with similar desktop systems [59, 86].

Apart from passive monitoring, employing eye tracking for interaction on handheld mobile devices can bring in many tangible benefits to the user. Being handheld, at least one of the user's hands is partially occupied throughout most interactions, thus limiting touch-based input. Furthermore, there are activities in which the user might not be able to operate a mobile device due to their hands being occupied, for example, when cooking or driving. Touch-based input is also limited in terms of reach – UI elements at the top of the interface are sometimes challenging to reach [11]. While there are voice-control alternatives for operating smartphones and tablets, they are not suited for situations when it is crowded or noisy. These are among the reasons why gaze has been deemed to be an attractive modality for interacting with handheld mobile devices. In addition to allowing hands-free interaction, there are particular use cases in which gaze outperforms other modalities, such as authentication [55, 74] and supporting disabled users [119].

Utility of Eye Tracking on Handhelds
While there has been prior classifications of eye tracking techniques and applications, such as Duchowski's survey of eye tracking applications [27], and the continuum of eye tracking applications by Majaranta and Bulling [77], our survey provides the first review of uses of eye tracking and eye-based interaction on handheld mobile devices. We discuss in-depth the application areas, as well as the chronological development of the adopted techniques. Prior research for mobile gaze interfaces broadly falls into three application domains: passive analysis of gaze behavior, implicit gaze interaction, and explicit gaze interaction.

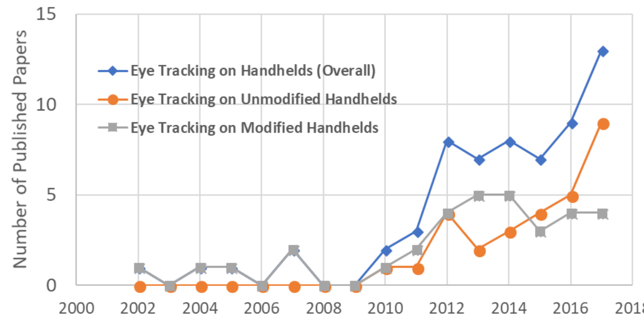

Figure 1. Research on eye tracking on handheld mobile devices started as early as 2002. Until 2010, researchers used external hardware (e.g., eye trackers, cameras, and processors) to process eye tracking data in real time. Advancements in hardware and gaze estimation methods inspired researchers switch attention fully on-device eye tracking. This is evidenced by an increasing number of contributions involving unmodified handhelds. The figure reflects the papers we reviewed - we reviewed all papers that involve eye tracking on mobile devices.

Gaze behavior analysis refers to the silent tracking of the user's eyes for later analysis. While eye tracking has been around in human-desktop interaction since the early 1980s [10], the unique context of handheld devices results in eye tracking uncovering behaviors that are different compared to those associated with desktop systems.

Implicit gaze interaction refers to interactive systems in which the system reacts to the user's natural eye behavior, without requiring the user to deliberately perform any explicit eye movements. This type of gaze-based interaction has been previously referred to as "passive eye interaction" [100], or attentive user interfaces [15, 110].

Explicit gaze-based interaction refers to the deliberate and conscious use of eye gaze to provide input. It can be further classified to (1) Gaze-only interaction, and (2) Gaze-supported interaction, i.e., multimodal interaction.

These classifications were developed after a detailed review of the 62 papers published about eye tracking published between 2002 and 2018. We first labeled each paper with a set of themes. Common themes were clustered to eventually develop the three aforementioned classifications.

History of Eye Tracking on Handhelds
We distinguish three phases in the history of eye tracking on handheld mobile devices. Like many research areas within HCI, researchers started investigating the opportunities brought forth by eye tracking on mobile devices as a novel technology in the early 2000s. Due to the limitations of mobile devices at that time, researchers used external cameras and processors, assuming that consumer devices will eventually catch up with research. We refer to this phase as the "past", and denote it by ■□□ in the following sections, to help readers navigate the paper. Commodity mobile devices then gradually started to feature better front-facing cameras and processors, driving the research community to explore eye-based interaction and eye tracking on unmodified handhelds. As shown in Figure 1, the last 3 years witnessed an ever-increasing number of contributions targeted to enabling seamless eye tracking

and gaze interaction on unmodified handheld mobile devices. We refer to this phase as the "present", and denote it by ■■□. Finally, the "future" phase is one where eye tracking is finally used daily in different contexts and scenarios rather than in the lab. We denote this phase by ■■■.

EYE TRACKING ON MODIFIED HANDHELDS ■□□

In the early 2000s, phone manufacturers started introducing front-facing cameras in handheld mobile devices. However, since these devices were mainly intended for video conferencing, their performance was often inadequate for real-time eye tracking. Specifically, these devices were limited in processing power, battery life, and resolution of the front-facing camera. The first works to explore eye tracking on handheld mobile devices overcame the hardware limitations in different ways. Some augmented the user by having participants wear a head-mounted eye tracker [35, 75, 87], while others augmented the device either by building their own hardware [24, 111, 85] or by using remote commercial eye trackers [25, 86].

Gaze Behavior Analysis ■□□

Previous work conducted gaze behavior analyses while reading [9, 24, 67, 83, 86], or while consuming user interfaces for usability analyses [59, 60, 61, 79, 80] on mobile interfaces. Most of these works relied on one of two approaches: using real mobile devices and simulating mobile devices.

Using Real Mobile Phones

In the first category, a mobile device was held by the participants while wearing a mobile eye tracker [18, 75, 86] or the mobile device was fixed on a holder while using a remote eye tracker or camera [9, 59]. For example, to track eye behavior during interaction with a mobile phone, Öquist and Lundin used a goggle-based system that consists of cameras and IR LEDs to track the user's eyes while using a cell phone [86]. They found that users prefer horizontal pagination over vertical scrolling. Biedert et al. used an eye tracker intended for desktop settings to track eyes of mobile device users while reading text on smartphones [9]. The mobile device was mounted on a holder, while the tracker was placed upside down behind it. This enabled them to identify recurrent behaviors; namely, they found that some users prefer reading one page at a time before scrolling to replace the entire page with new content. Others read line by line and scrolled almost constantly to keep information flowing to a preferred area. The majority of their participants preferred blockwise scrolling in which they change parts of the screen every now and then. Kunze et al. described their vision to quantify reading activities by tracking eyes on tablets and phones [67].

Eye tracking is a capable tool for usability analysis [45]. This motivated many researchers to explore the usability of UIs on handhelds. Kim et al. studied different aspects of UI design when displaying search results on mobile devices [58, 60]. They used a commercial remote eye tracker and a smartphone fixed on a holder. They found that gaze behavior is different when viewing search results on a large screen compared to a smaller mobile screen; on smaller screens, users scan the results narrowly with fewer skips and less frequent changes in scan direction, and tend to read from top to bottom. In another study, they made a similar observation to that by Öquist and Lundin [86]; they found that users prefer horizontal pagination over vertical scrolling when browsing search results on mobile devices, most likely due to its resemblance of flipping book pages [59]. In follow up work, they found that users scan almost a similar number of links when search result snippets are longer, making the search task longer; hence, unlike desktop settings, shorter search result snippets are more suitable for mobile settings [61].

Simulating Mobile Devices

In the second category, gaze behavior on mobile devices was studied without using mobile devices at all. Instead, simulators that run on desktop computers were used. For example, Cuadrat Seix et al. studied gaze behavior when using an Android emulator that ran on a desktop computer, to which an eye tracker was connected [22]. The size of the emulator's screen was adapted to match that of a smartphone. A similar approach was adopted in multiple studies [20, 58, 79, 80, 95]. Several works explored cross-platform usability [23, 94], where usability across several platforms, including handheld mobile devices, was evaluated and compared [79, 80]. For example, Majrashi et al. identified eye movement patterns associated with cross-platform usability issues, i.e., usability problems related to switching from an interface to another [80].

Implicit Gaze Interaction ■□□

As early as 2005, Dickie et al. introduced eyeLook, a system to detect eye contact with a mobile device [24]. They presented two applications of eyeLook. The first is seeTV, where a mobile device that plays a video automatically pauses content when the user is not looking. The second is seeTXT, which employs Rapid Serial Visual Presentation (RSVP) by showing and advancing text only when the user is looking at the mobile device's screen. They augmented a mobile phone with wireless eye contact sensors to detect when the user looks at the display [24]; a proxy server coordinated between the sensor data and the mobile apps wirelessly via bluetooth or GPRS. GeoGazemarks [35] presented users with a history of their visual attention on maps as visual clues to facilitate orientation. Showing the Gazemarks significantly increased the efficiency and effectiveness during map search tasks, compared to standard panning and zooming. The authors employed a head-mounted eye tracker to create GazeMarks when viewing a map on a mobile device [35]. Paletta et al. presented a toolkit to assist developers in eye tracking on handheld mobile devices when the user is wearing an SMI eye tracker [87, 88].

Explicit Gaze Interaction ■□□

Explicit gaze-based interaction on handheld mobile devices can be classified to (1) gaze-only interaction, and (2) gaze-supported (multimodal) interaction.

Gaze-only Interaction

Work on gaze interaction with handheld mobile devices adopted a number of techniques for gaze-only interaction. For example, researchers used commercial eye trackers to compare dwell time and gaze gestures on mobile devices; they found that gestures are faster, less error-prone and better perceived by users [25, 28, 97]. To perform this comparison, Drewes

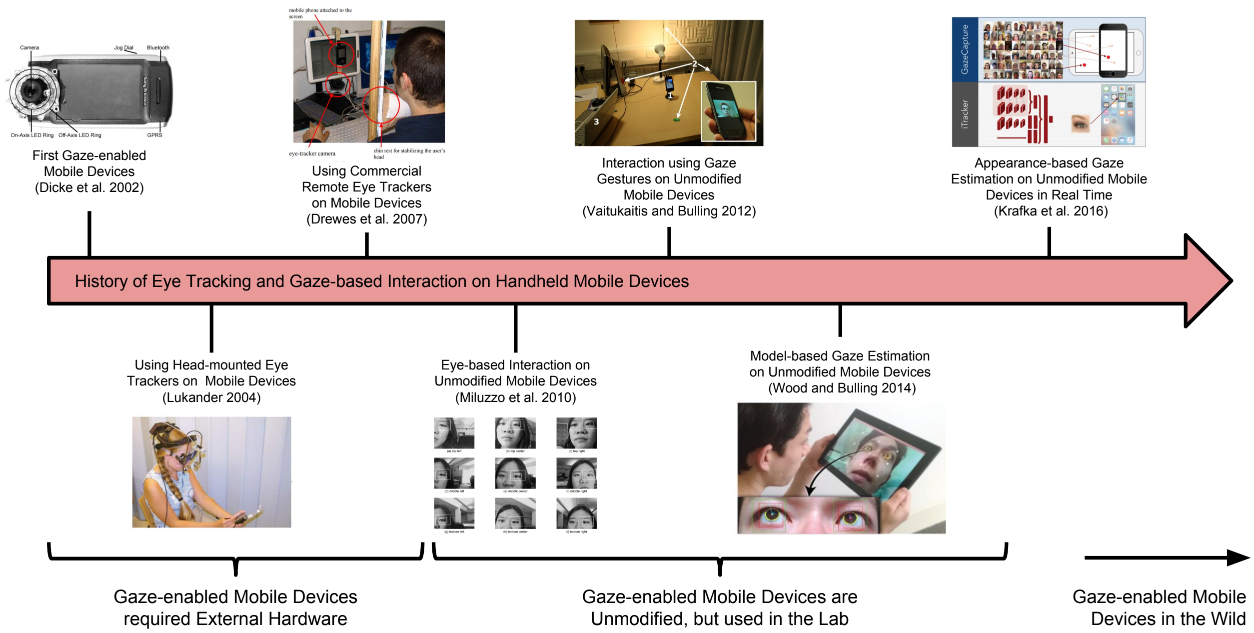

Figure 2. Eye Tracking and Eye-based Interaction on handheld mobile devices required external hardware in the past. Recent advancements in processing power of off-the-shelf devices, and their front-facing cameras made eye tracking and eye-based interaction feasible on unmodified handhelds. At this stage, the next step is pervasive eye tracking on handheld mobile devices in the wild. Note that the purpose of this figure is to visualize the developments and what is feasible with each period's technologies. Yet, there are many present-day works that still augment handhelds with additional hardware for eye tracking.

et al. [25] attached a mobile phone to a screen under which an eye tracker was stationed and users had to use a chin-rest (see Figure 2), while Dybdal et al. attached a breadboard with six infrared LEDs above a mobile phone, and placed a webcam close to the location of the front-facing camera [28]. The camera was connected to a separate computer, and gaze coordinates were sent back to the phone via WiFi. Rozado et al. also experimented with gaze gestures on mobile devices; they modified a smartphone by attaching a camera and IR LEDs to its bottom [98]. More specifically, they attached a webcam to the bottom of a smartphone, and a set of IR LEDs to the bottom right to detect gaze gestures [98]. Previous work showed that vibrotactile feedback significantly improves the use of gaze gestures in terms of efficiency and subjective experience, mainly because it helps users confirm if input was recognized, and cope with errors [49, 96]. To study that, Kangas et al. built a contact list app that users can navigate via gaze gestures, and detected the gestures using a commercial desktop eye tracker [49].

While the aforementioned works used video-based eye tracking [77], Valeriani and Matran-Fernandez detected EOG signals by attaching electrodes on the user's face, enabling them to leverage eye winks for interaction [109]. The electrodes were connected to an OpenBCI board which communicated with a laptop via Bluetooth, which in turn performed the processing and forwarded commands to the smartphone via WiFi.

Gaze-supported Interaction

A second line of work focused on gaze-supported interaction on mobile devices, where gaze was used alongside another modalities. Nagamatsu et al. introduced MobiGaze, where users gaze at areas that are unreachable by the index finger on a mobile device screen, then tap anywhere on the touchscreen to activate the area being looked at [85]. They attached stereo cameras and an IR-LED to a mobile device, and performed the image processing on a laptop that is tethered to the cameras and connected wirelessly to the mobile device. Pfeuffer and Gellersen attached a Tobii EyeX tracker to the bottom of a Microsoft Surface Pro tablet to experiment with multimodal interactions on a handheld tablet [90]. For example, the user could pinch and zoom at the location they are gazing at, while performing the touch gestures elsewhere on the interface. Turner et al. introduced a series of systems for cross-device content transfer; using a head-mounted eye tracker, they explored transferring content from public displays to handheld mobile devices by, for example, gazing at the item on the display, and then tapping on the mobile device to transfer the content to said device [105, 106, 107]. Zhou and Velloso experimented with multiple concepts for input using eye tracking with back of the device interaction [124].

Lessons Learned ■□□

While the use of remote eye trackers allowed researchers to overcome some of the hardware limitations, this approach offered only limited ecological validity. Head-mounted eye trackers, especially in their early days, were cumbersome to wear, and required knowledge of the device's bounds by, for example, marking the corners of the mobile device [35] or performing edge detection [87], in order to map gaze points to locations on the device's screen. Finally, perhaps the most impeding disadvantage of head-mounted eye trackers is that they were not yet commonly worn by users; it is not feasible to conduct field studies in which the handheld device is "mobile". On the other hand, researchers who built their own prototypes had a lot of flexibility. However it was often challenging to identify the reasons behind unexpected behavior since the prototypes were often not rigorously tested. Those who used commercial remote eye trackers had the advantage that the technical performance had already been evaluated. The availability of technical specifications of trackers makes results from different studies relatively easy to compare.

On the downside, the vast majority of studies that used remote eye trackers had the device fixed on a mount rather than held by the user, hence reducing the ecological validity of the results. Ecological validity problems become even more prominent when using on-screen simulators, since all the form-factor related aspects are lost in that case. This is especially the case when the user needs to interact with the interface; even if a touchscreen is used while simulating the interface on a computer screen [22], interacting with a vertical mobile interface at eye's height is not usual when using an actual mobile device. Moreover, remote eye trackers are often placed below the device's screen, making it more likely that the user will occlude the camera's view with their hands or arms when interacting or holding the device, which in turn results in losing track of the user's eyes.

In terms of explicit interaction, a clear message from a large body of early work is that interaction using eye behavior (e.g., gestures [26], smooth pursuit [113]) is a more promising direction than interaction by dwell time [25, 28, 97]. Gestures and Pursuits are not only better perceived than dwell time, but they are easier to implement since they do not require accurate gaze estimates, which in turn means that they are less reliant on calibration [26, 113]. This is an important advantage, since the mobile nature of handhelds makes it likely that calibration would break often.

To summarize, we can make the following conclusions from the discussed body of work:

- The use of external hardware or simulators limits the ecological validity of study results.
- Rather than using traditional dwell time for explicit interaction, leveraging eye behaviors, such as smooth pursuit or gaze gestures, is a more promising direction for handhelds.

EYE TRACKING ON UNMODIFIED HANDHELDS ■■□

Prior works that utilized external eye trackers were the first to analyze gaze behavior on mobile devices and hence made a myriad of interesting findings. However, this was at the expense of lower ecological validity. In 2010, researchers started considering eye-based interaction using unmodified mobile devices [84]. The interest in enabling eye-based interaction and even fine-grained gaze estimation on handhelds increased exponentially since then (see Figures 1 and 2).

Gaze Behavior Analysis ■■□

Several approaches for gaze estimation on unmodified mobile devices were proposed in the last 5 years. They can be classified to model-based and appearance-based gaze estimation.

Model-based Eye Tracking on Unmodified Handhelds

Researchers investigated model-based approaches for gaze estimation on unmodified handheld devices. In model-based approaches (also referred to as geometric-based approaches), the system leverages the visible features of the user's face and eyes (e.g., pupil center, eye corners, etc.) to build a geometric model of the user's eyes, and estimate the gaze direction by extending a vector from the center of the user's eyeball, going through the center of the pupil, and eventually intersecting the screen at the gaze point. For example, in EyeTab, Wood and Bulling employed a model-based approach by detecting the eye positions, followed by a 2D limbal ellipse fitting procedure, and then finally projecting a gaze vector to estimate where it intersects the screen [117]. Their approach was evaluated on a tablet and ran near-realtime with an accuracy of 6.88 degrees at 12 Hz without the need for calibration. The EyeTab system was further evaluated and ported to Android by Hohlfeld et al. [38], but accuracy dropped to 15 degrees of visual angle.

While the aforementioned works focused on tablets, Michael X. Huang et al. proposed a novel approach to estimate gaze on smartphones by leveraging the reflection of the screen on the user's cornea [41]. In their approach, called ScreenGlint, they perform face detection followed by extraction of the iris and estimating its center, and then the brightest reflection closest to the iris center with a perimeter less than 60 pixels is assumed to be the glint of the smartphone's screen. Afterwards, they use some features including interpupillary distance and glint-iris vectors of both eyes, and then utilize Gaussian Processes [99] for regression to estimate on-screen gaze coordinates. Kao et al. overcame the hardware limitations of an Android mobile device by performing the heavier part of the computation on the cloud [50]. Namely, face detection was done on the client, while blink, iris and eye features detection, as well as the gaze mapping done by a neural network, were all performed on the cloud, which in turn sent the gaze coordinates back to the client's device.

Appearance-based Eye Tracking on Unmodified Handhelds

Another body of work employed appearance-based approaches, that is, approaches that employ machine learning based on training datasets, in order to map eye images directly to gaze coordinates. For example, Holland et al. [39, 40] used the front-facing camera of a commodity tablet to perform face and eye detection using Haar classifiers [114], followed by iris detection, and then finally applied a neural network of two layers to map the image of the iris to a gaze coordinate on the screen. They achieved a 3.95 degrees accuracy at a sampling rate of 0.7 Hz. Ishimaru et al. also employed an appearance-based approach and achieved 12.23 mm accuracy at 30 cm in their setup using user-dependent training [44]. The authors do not report the accuracy in degrees of visual angle, but with the given setup parameters, it can be estimated to be 2.26 degrees. Face, eye, and iris detection were done using CIDetector (iOS's face detection library), and then eye corners were detected using the Harris corner detection method [112]. The inner eye corners and image coordinates of both irises were used to calculate the gaze coordinate by regression. Krafka et al. introduced iTracker, which estimates gaze with an end-to-end appearance-based approach, i.e., without utilizing any features such as head pose or eye center location [66]. Their model is based on Caffe, a framework for deep learning algorithms [47]. They achieved an accuracy of 2.58 degrees on unmodified iPhones and iPads. Qiong Huang et al. applied an appearance-based approach to estimate gaze on unmodified tablets [42]. Their approach started by image normalization, followed by feature extraction and regression. They experimented with different features and tested four regressors. Using multilevel histograms [78] as features and a random forest [12] as a regressor yielded best results—3.17 cm in their setup. The accuracy cannot be reported in degrees due to the varying user-to-screen distance in the study.

Implicit Gaze Interaction ■■□

The previous implicit gaze systems used external eye trackers or augmented the mobile device. Recent works performed implicit gaze interaction on unmodified mobile devices.

Song et al. introduced Eye Veri, an implicit biometric authentication scheme [101]. In EyeVeri, fixations and saccades are detected from the front-facing camera of a smartphone in response to on-screen visual stimuli. Illegitimate users are locked out automatically since their gaze behavior is different than that of the legitimate one. The system first detects the face position using six-segmented rectangular filter [51], and then eye and iris positions are determined. After that, a gaze vector is projected from the estimated center of the eye ball through the center of the iris to eventually estimate a gaze point on the screen. While they do not report the accuracy of gaze estimation, they reported the sampling rate to be 5 Hz, and the accuracy of the system in terms of allowing access to the legitimate user—it was between 67.95% and 88.73%, depending on the shown stimuli.

Another implicit gaze-based system is SwitchBack, which used the front-facing camera to determine if the user is not paying visual attention to the device to pause the task and help them resume it when they gaze back at the device [83]. The system relied on the number of frames between each two consecutive saccades to determine whether the user is reading on-screen text or if they looked away from the display. SwitchBack achieved a mean absolute error of 3.9% in determining the line the user is currently reading. In another project, Mariakakis et al. measured the pupil diameter in response to a smartphone's flashligh using its rear camera [82]. They used a convolutional neural network to find the pupil diameter and achieved a median error of 0.3 mm. Jiang et al. presented VADS, a system that allows users to interact with objects in the environment by holding an unmodified handheld device in a way such that the rear camera sees the object, and the front camera sees the user's face [48]. They used an optimized version of Active Shape Models (ASM) [21] for face tracking, followed by EPnP [71] to estimate the face pose, the iris center is then detected, and finally a gaze vector is estimated via linear regression. By knowing which smart object the user is looking at, the object can react to the user.

Explicit Gaze Interaction ■■□

Recent systems detected gaze input directly through the front facing camera. EyePhone by Miluzzo et al. was among the first works about eye-based interaction with unmodified mobile devices [84]. EyePhone enabled eye-based interaction by moving the phone relative to the user's face such that the user's left eye is in one of 9 possible positions in a 9-grid, and then blinking to trigger input. The approach employed template matching for detecting the eye and its position. While they used existing algorithms intended for desktop scenarios, they adapted them to match the reduced computation speed and camera resolution of the N810 phone they used. A more recent system, Reflector, utilizes the user's reflection on the screen by using a face feature (e.g., right eye) as a virtual cursor for performing selections [70]. The system estimates the reflected image through the front-facing camera, and is then calibrated using one of the user's eyes as a cursor to perform 9-point calibration.

Several systems that detect gestures through the camera of unmodified handheld devices were also introduced [33, 32, 52, 49, 72, 108, 119]. Vaitukaitis and Bulling detected gaze gestures in near real-time with an accuracy of 60% on an unmodified Android smartphone [108]. The experiment was done in a controlled setting in which the lighting conditions were constant and the smartphone was mounted on a dock. In GazeSpeak, Zhang et al. detected gaze gestures in four directions as well as blinks to allow the disabled to communicate using the rear camera of an unmodified mobile device [119]. To do so, they had each participant calibrate by performing blinks and gaze gestures in all directions. Gaze gestures were then classified by matching the normalized eye images extracted from the video in real time to the templates stored during calibration. The template with the lowest mean squared error to the detected gesture is deemed to be the closest match. The accuracy of the system was 89.7% without corrective lenses, 89% with corrective lenses, and 80.4% with glasses. In Gazture, Li et al. introduced gaze-based gesture control on tablets by first estimating gaze in low accuracy but in real time, and then recognize gaze gestures [72]. Their system supported 8 directions, detected through a sliding window that gradually detects and refines the detected direction. Gestures were recognized successfully 82.5% of the time at a distance of 50 cm, and 75% of the time at a distance of 70 cm.

Multimodal systems were also implemented on unmodified handhelds. Khamis et al. proposed a series of multimodal authentication schemes for unmodified mobile devices in which users entered passwords and PINs using both touch input and gaze gestures [52, 55, 56]. In their approach, the face and eyes were detected using a Haar classifier [114], and then the ratio of the distances between each eye and the center of the face was used to determine if the gaze gesture was to the left or to the right. Depending on the configuration, their systems achieved accuracy between 60% and 77%. Another series of multimodal systems were by Elleuch et al., who proposed interaction with unmodified mobile devices using gaze gestures to four directions [32, 33], as well as using gaze gestures alongside mid-air gestures that are also detected through the front-facing camera of a smartphone [34]. The system detects faces using Haar cascade classifier [114]. Pupil positions are then compared across consecutive frames to detect gazes upwards, downwards, left and right.

While promising, only few work leveraged smooth pursuit eye movements on mobile devices. Liu et al. proposed a unimodal authentication scheme for unmodified mobile devices where the user follows the trajectory of one of 4 moving on-screen targets via smooth pursuit eye movements [74]. They employ the Pearson correlation to measure the similarity between the eye movements and movements of the on-screen targets (as in [113]). The average authentication accuracy was 91.6%.

Lessons Learned ■■□

Eye tracking and eye-based interaction using front-facing cameras of commodity devices opens doors for a multitude of opportunities. For example, it allows field studies to investigate gaze behavior in the wild, it enables usability testing outside labs, and empowers users with novel input methods. Nevertheless, further improvements in gaze estimation on unmodified devices is needed. Many of the proposed gaze estimation methods were evaluated in settings where the device was mounted on a holder. And some highly accurate approaches were not tested in real time [41]. Even though gaze-based interaction (e.g., by gestures or smooth pursuit eye movement) has been achievable in real time, researchers and practitioners need to deal with issues pertaining to the user's holding posture of the handheld device. Nonetheless, with more commodity devices adopting depth cameras (e.g., iPhone X and Google's project Tango), and increasing processing power that allows performing complex calculations directly on the device, the future is promising for eye tracking on unmodified handhelds.

To summarize, we can draw the following conclusions:

- Eye Tracking and eye-based interaction are feasible on unmodified mobile devices, and are expected to improve even further.
- Researchers are facing different types of challenges now. For example, users do not always hold devices in a way that allows the camera to see their eyes.

THE FUTURE OF EYE TRACKING ON HANDHELDS ■■■

The impeding challenges in the early days of eye tracking were mostly hardware-related. Nowadays, advances in visual computing, front-facing cameras, and processors on handheld mobile devices make eye tracking an app-installation away.

Furthermore, the advent of front-facing *depth* cameras is a turning point that will take eye tracking from research labs to consumer mobile devices that are used daily in the wild. While eye tracking on commodity devices was so far evaluated on mobile devices that use RGB front-facing cameras, all of the discussed techniques are not only applicable to depth front-facing cameras such as those of Project Tango and iPhone X, but are expected to yield even better results. For example, the geometric modeling of the eyes, and the extraction of the user's face and eye images can both be significantly improved with the use of depth imaging [36, 118].

The discussed developments are expected to have a significant impact on Mobile HCI research. However, even with the major hardware limitations almost overcome, some unique aspects of handheld devices pertain to impose challenges to eye tracking and gaze-based interaction on said devices. Now that eye tracking on handhelds is on the verge of becoming pervasive, *novel challenges and opportunities* arise. Further research is needed to address the challenges, and opportunities can be leveraged to expand our knowledge of user behavior, and enhance the user experience of handhelds.

Opportunity: Eye Tracking on Handhelds in the Wild

High quality gaze estimation on unmodified handheld mobile devices sets the scene for wide scale eye tracking studies in the wild. Although field studies are one important research method in Mobile HCI [63, 64], eye tracking for analysis of gaze behavior on mobile devices has always been conducted in the lab. For the first time, we will be able to conduct ecologically valid field studies where users' gaze behavior is tracked in every day life scenarios. For example, this will allow us to study gaze behavior when using location-based services; previous work could not achieve that due to participants being required to stay in the lab, or even at a fixed distance from a "mobile" device that is held by a mount. Usability analysis can now cover contexts that were never studied before, such as how users perceive websites and mobile apps while commuting, while walking, or while engaging with others in conversations.

Pervasive advertising is another interesting opportunity. Gaze data analysis can reveal if users see advertisements, if placement of ads is ideal, and could reveal potential interests that can be used to tailor advertisements. Advances in this direction could potentially encourage manufacturers of handheld devices to invest in integrating cameras with wider lenses, or employ movable cameras that would enable active eye tracking (e.g., setting focus on the user's eyes [57]). On the downside, this comes with privacy implications, which we discuss later.

Opportunity: Making Eye Tracking Concepts Mobile

Future work in gaze-based interaction on handheld mobile devices can go beyond labs and provide tangible benefits in the wild instead.

In the simplest form of implicit gaze interaction, attention detection can be leveraged to save battery life and protect privacy by turning off the screen when the user looks away [100]. While existing works enhanced reading experiences on unmodified handhelds [83], there is a wide range of applications that are yet to be explored. Biedert et al. explained their vision of how eye tracking can be leveraged for attentive text [8]. Many of these concepts were never realized on handheld mobile devices, mainly because the technology was not mature enough to perform reliably. These concepts can now be adapted or even extended to fit the mobile context. For example, some works proposed protecting private content on large public displays by estimating gaze direction of bystanders to alert the user of potential shoulder surfers [1, 14, 123]. Now these approaches can be deployed on unmodified mobile devices, and evaluated in public settings where shoulder surfing actually occurs the most (e.g., in public transport [31]).

Furthermore, implicit gaze can facilitate interaction on touchscreens of handhelds, which are continuously increasing in size, making it challenging to reach out for far UI elements at the edges of the screen via touch. Some existing systems use touch gestures to reach the top of the interface [43]. Future

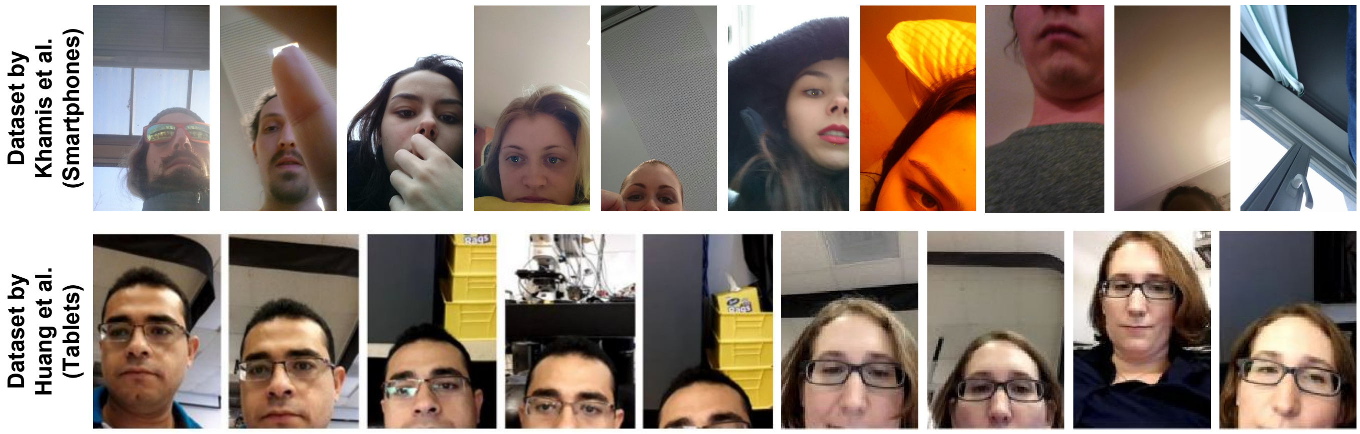

Figure 3. Datasets of photos taken from the front-facing cameras of smartphones in the wild (top), and tablets in the lab (bottom) indicate that the user's entire face is not always visible in the cameras' view. This has implications on eye tracking since many gaze estimation methods require detecting a full-face (Figures adapted from: [42, 53])

systems could detect if the user is reaching out for far targets through their gaze, and bring them closer to the user's dominant hand. Gaze can be leveraged implicitly for correcting for parallax errors [54], which is a problem on touchscreens, particularly when styli or pen-shaped instruments are used [69]. Cognitive load can be estimated through the pupil's diameter [91], blink rate [29], or smooth pursuit eye movements [65].

Explicit gaze interaction on mobile devices can provide many tangible benefits. Users could navigate through albums using gestures [121], unlock phones using gestures [52, 55, 56], or smooth pursuit [74]. Users could navigate installed applications, answer calls, speed dial, and respond to system prompts by eye movements. Although gestures and smooth pursuit might require more cognitive effort than natural eye movements, they are promising for gaze-based input on handhelds because they are robust against gaze estimation inaccuracies [16]. Moreover, many types of eye movements are promising for handheld mobile devices, but were never exploited before. For example, Optokinetic Nystagmus are eye movements that combine saccades and smooth pursuits. They were demonstrated to be promising for interaction in desktop scenarios, and they also show promise in mobile context [46]. Eye vergences, which are simultaneous movements of both eyes in opposite directions, can also be exploited for interaction. In particular, convergences were used for gaze input [62], but were never explored for mobile devices. Vestibulo-ocular-reflex (VOR) is a reflex action that takes place when humans fixate at a target and move their heads; humans can remain focused on the target despite their head movements, since the eyes reflexively compensates for the head movements by moving in the opposite direction of the head. VOR was exploited to detect head gestures, in an approach called eye-based head gestures [81, 93]. Detection of VOR is as straightforward as detecting gaze gestures, since the reflex can be seen from the camera's perspective as a gaze gesture to the direction opposite to the head movement's direction.

Challenge: Holding Posture and Face Visibility

Users hold their handheld devices in different ways. Previous work suggested that the user's activity (e.g., running apps) affects the way they hold their phone [13, 53, 115], hence influencing the visibility of their faces and eyes in the front-facing camera's view (see Figure 3), which in turn influences the reliability of eye tracking on handheld devices. This problem is amplified by the fact that many gaze estimation algorithms require full-face images [5, 37, 72, 102, 116, 120].

Researchers have investigated how often the user's face is visible in the front-facing camera's view. Khamis et al. collected a dataset of 25,726 photos taken from front-facing cameras of smartphones used in the wild [53]. In their dataset, the user's full face was visible in only 29% of the taken photos, while the eyes were visible in 48% of the photos. In the vast majority of the dataset, the face is either partially hidden due to the angle from which the phone is held, the range of the lens, or occlusions by the user's hands, hair, or tools. Some of the photos in their dataset are labeled with the holding posture of the user (e.g., dominant hand vs non-dominant hand vs both hands), in addition to the state of the user (e.g., standing, walking, sitting). While Khamis et al.'s dataset focused on photos from smartphones used in the wild, Huang et al. collected a dataset from tablets used in controlled settings, in which participants were standing, sitting, slouching, or lying down [42]. Despite being collected in the lab, the full-face was visible in only 30.8% of the photos in their dataset, suggesting that the problem is also prominent on tablets, which are held differently than smartphones [13]. Figure 3 shows examples of photos taken from front facing cameras of handheld devices. Other works also investigated eye tracking when the user is sitting at a table, sitting on a chair, slouching on a chair, sitting on the floor, lying prone, lying supine, standing, and walking [41].

Research Directions

Although hand postures are different across smartphones and tablets [13], the problem of face visibility is prominent in both cases [42, 53]. Khamis et al. [53] proposed borrowing concepts from research on user guidance in front of public displays to address this problem. Users can be guided to the optimal position of holding a phone by using a face outline overlaid on a mirror video feed [122], or by distorting the view and deblurring it as the user is implicitly guided to the correct position before the screen can be seen clearly [3].

Khamis et al. found that it is more likely that both of the user's eyes are visible to the front-facing camera, opposed to the full face [53]. This means that gaze estimation algorithms that assume that the user's full face is entirely visible [5, 37, 72, 102, 116, 120] are not well suited to the dynamic nature of handheld mobile devices. There is a need to further investigate methods that rely on the eyes only for gaze estimation and not the entire face. For example, appearance-based methods can perform better by using eye images for training rather than full face images. There are also approaches for gaze estimation that are based on the whites of the eyes [7], which might be more suitable for this context.

Challenge: User's Clothing and Accessories

A conceptual problem that affects eye tracking is that mobile devices are often used outdoors, and depending on the weather conditions users could be wearing scarfs that partially occlude the face, or sunglasses that occlude the eyes (see Figure 3).

Research Directions

This problem is similar to the problem of interacting with mobile devices via touch while wearing gloves; unless conductive gloves are worn, users need to take off handwear before they can provide touch input. Similarly, users might need to take off sunglasses that completely obscure the eyes. However with Eyewear computers becoming indistinguishable from regular daily eyewear [17], future sunglasses can already have eye trackers integrated within them, and communicate gaze information to the mobile device directly. Another more daring solution is to visualize the user's eyes on the surface of the eyewear, in order for the front-facing camera to detect it and estimate gaze; there has been work on visualizing the user's eyes on the front-facing surface of head-mounted displays (e.g., VR headsets) to facilitate communication with people surrounding the user [19, 76].

Challenge: Calibration and Shaky Environments

Many approaches for gaze estimation either require calibration [41], or improve significantly with calibration [66]. Systems that require calibration would likely need to be recalibrated if the user's posture changes amid interaction. Even if the user holds the device in the same way, inevitable shaking of the device would make the calibration data obsolete.

Research Directions

Calibration is known to be tedious and time consuming, but is nevertheless useful for accurate gaze estimation [77]. Pino and Kavasidis worked around the shaking device problem by leveraging the device's inertial sensors to determine if the current posture is different, and accordingly decide whether to collect new eye images or to use the last collected ones [92]. Li et al. also exploited the accelerometer to selectively determine which frames to use for gaze estimation [73]. A clever approach would be to automatically compensate for the changed posture to avoid the need to recalculate parameters.

For interactive applications, a plausible approach is to use gaze interaction techniques that do not require calibration such as gaze gestures [26], smooth pursuit eye movements [113], Vestibulo-ocular-reflex [81], convergence [62], and optokinetic nystagmus [46].

Challenge: Lighting Conditions

Majaranta and Bulling classified eye tracking techniques to Video-based, Infrared-based Pupil-Corneal Reflection (IR-PCR), and Electrooculography (EOG) [77]. Video-based eye tracking is done using RGB cameras, which are the most commonly used for front-facing cameras on mobile devices today. This technique's disadvantage is that it does not work in the dark, and might misbehave if part of the user's face is exposed to more light than the other, or if the user is wearing make-up, contact lenses or eye glasses. On the other hand, IR-PCR works better in the dark and is more robust against varying light conditions. Incorporating IR emitters and IR sensors—the building blocks for IR-PCR eye tracking—into commercial mobile devices is increasingly becoming common (e.g., Project Tango and iPhone X). However the technique often breaks down in sunlight because of its interference with the IR sensors. On the other hand, EOG is not influenced by light conditions, and can even work while the user's eyelids are shut [77]. However due to the need to attach electrodes on the user's skin, it has rarely been investigated in the context of mobile devices. The only exception is the work of Valeriani et al. who detected eye winks on smartphones using EOG [109].

Research Directions

Lighting conditions has always been a challenge in eye tracking research, and will remain a challenge in eye tracking on handhelds. Particularly because mobile devices are often used in public and areas of varying light conditions. Research in this direction can investigate how to preemptively detect situations where eye tracking would fail and warn or inform that user. For example, mobile devices are often equipped with light sensors; using them to determine if the surrounding light conditions are suitable for eye tracking, and then providing the user with an alternative modality if needed or fallback to video-based eye tracking, could be a way to mitigate the impact of the problem.

Challenge: Privacy Concerns

Although they might not always have the necessary technical knowledge to understand the privacy risks behind certain technologies, privacy-aware users are willing to take additional measures to protect their privacy [30]. This means that some users might not be willing to allow eye tracking on their mobile devices, lest it puts their privacy at risk. Users already show discomfort knowing that mobile apps that have persmissions to access the camera can be taking pictures all the time [53]. This concern is not unjustified. Gaze behavior can reveal many things about the user, including but not limited to their visual attention [89, 103], mental illnesses [6], neurological disorders [104], and corneal reflections can be even used to learn about third parties (e.g., who the user is looking at [68]).

Research Directions

Being ubiquitous, the thought of tracking the user's eyes through mobile devices anywhere and at any time might intimidate users. To reassure them that their eyes are tracked only when needed, existing approaches that have been proposed to alert users when private data is shared wit an app can be used [2, 4]. Another way to reassure users is to process images on the fly without storing them or uploading them on to the cloud.

To make sure this practice is enforced, app stores could require app developers to make their code open source. Although this will not help the average user to identify whether or not a mobile app violates their privacy, there has been cases in the past where developers and enthusiasts found loopholes in open source software and made them public, which in turn informed average users. Similar to how certificate authorities are employed in HTTPS certification, mobile apps could be certified by trusted entities that they do not violate privacy. Another research direction is to try to understand privacy perceptions of users of eye tracking on handheld mobile devices. Another direction is to try to better understand the users' changing notion of privacy amidst technologies.

Other Challenges

Being mobile devices that need to be charged periodically, eye tracking on handhelds needs to be highly optimized to reduce battery consumption. Battery capacities are continuously increasing, and faster methods for charging handhelds are now available. However, if eye tracking algorithms are to continuously process the front-facing camera feed, future optimization to reduce battery consumption are needed. Furthermore, algorithms that require less processing power would in turn lessen the device's overheating.

CONCLUSION

Mobile HCI research is on the verge of new possibilities that were never available before. We were able to identify challenges and opportunities after a literature review, where we investigated how researchers approached eye tracking on handhelds in the past, and how advances allowed eye tracking to take place on unmodified devices. Eye tracking on handheld mobile devices are now feasible, allowing researchers to investigate novel use cases, and explore areas that were never possible before. For example, studies of gaze behavior in response to advertisements, apps, websites, etc. is now feasible in the wild and not only in labs. Gaze-based interaction can provide tangible benefits to the user by simply installing an app on their personal off-the-shelf handheld mobile device, especially by using gestures, smooth pursuit and other eye behaviors for interaction. We have also provided recommendations and identified directions for future research to address novel challenges in this context; we need to investigate ways to accommodate to cases where the user's face is completely or partially hidden from the front-facing camera's view, and we need to understand the privacy perceptions of users of eye tracking mobile applications.

ACKNOWLEDGEMENTS

This work was funded, in part, by the Cluster of Excellence on Multimodal Computing and Interaction (MMCI) at Saarland University, Germany, and by the Bavarian State Ministry of Education, Science and the Arts in the framework of the Center Digitization.Bavaria (ZD.B). This research was supported by the German Research Foundation (DFG), Grant No. AL 1899/2-1.

REFERENCES

1. Mohammed Eunus Ali, Anika Anwar, Ishrat Ahmed, Tanzima Hashem, Lars Kulik, and Egemen Tanin. 2014. Protecting Mobile Users from Visual Privacy Attacks. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication (UbiComp '14 Adjunct)*. ACM, New York, NY, USA, 1–4. DOI: http://dx.doi.org/10.1145/2638728.2638788
2. Hazim Almuhimedi, Florian Schaub, Norman Sadeh, Idris Adjerid, Alessandro Acquisti, Joshua Gluck, Lorrie Faith Cranor, and Yuvraj Agarwal. 2015. Your Location Has Been Shared 5,398 Times!: A Field Study on Mobile App Privacy Nudging. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. ACM, New York, NY, USA, 787–796. DOI: http://dx.doi.org/10.1145/2702123.2702210
3. Florian Alt, Andreas Bulling, Gino Gravanis, and Daniel Buschek. 2015. GravitySpot: Guiding Users in Front of Public Displays Using On-Screen Visual Cues. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology (UIST '15)*. ACM, New York, NY, USA, 47–56. DOI: http://dx.doi.org/10.1145/2807442.2807490
4. Rebecca Balebako, Jaeyeon Jung, Wei Lu, Lorrie Faith Cranor, and Carolyn Nguyen. 2013. "Little Brothers Watching You": Raising Awareness of Data Leaks on Smartphones. In *Proceedings of the Ninth Symposium on Usable Privacy and Security (SOUPS '13)*. ACM, New York, NY, USA, Article 12, 11 pages. DOI: http://dx.doi.org/10.1145/2501604.2501616
5. Tadas Baltrušitis, Peter Robinson, and Louis-Philippe Morency. 2016. OpenFace: An open source facial behavior analysis toolkit. In *2016 IEEE Winter Conference on Applications of Computer Vision (WACV)*. 1–10. DOI: http://dx.doi.org/10.1109/WACV.2016.7477553
6. Philip J. Benson, Sara A. Beedie, Elizabeth Shephard, Ina Giegling, Dan Rujescu, and David St. Clair. 2012. Simple Viewing Tests Can Detect Eye Movement Abnormalities That Distinguish Schizophrenia Cases from Controls with Exceptional Accuracy. *Biological Psychiatry* 72, 9 (2012), 716–724. DOI: http://dx.doi.org/10.1016/j.biopsych.2012.04.019
7. Pascal Bérard, Derek Bradley, Maurizio Nitti, Thabo Beeler, and Markus Gross. 2014. High-quality Capture of Eyes. *ACM Trans. Graph.* 33, 6, Article 223 (Nov. 2014), 12 pages. DOI: http://dx.doi.org/10.1145/2661229.2661285
8. Ralf Biedert, Georg Buscher, Sven Schwarz, Jörn Hees, and Andreas Dengel. 2010. Text 2.0. In *CHI '10 Extended Abstracts on Human Factors in Computing Systems (CHI EA '10)*. ACM, New York, NY, USA, 4003–4008. DOI: http://dx.doi.org/10.1145/1753846.1754093
9. Ralf Biedert, Andreas Dengel, Georg Buscher, and Arman Vartan. 2012. Reading and Estimating Gaze on Smart Phones. In *Proceedings of the Symposium on Eye*

Tracking Research and Applications (ETRA '12). ACM, New York, NY, USA, 385–388. DOI: http://dx.doi.org/10.1145/2168556.2168643

10. Richard A. Bolt. 1981. Gaze-orchestrated Dynamic Windows. *SIGGRAPH Comput. Graph.* 15, 3 (Aug. 1981), 109–119. DOI: http://dx.doi.org/10.1145/965161.806796
11. Sebastian Boring, David Ledo, Xiang 'Anthony' Chen, Nicolai Marquardt, Anthony Tang, and Saul Greenberg. 2012. The Fat Thumb: Using the Thumb's Contact Size for Single-handed Mobile Interaction. In *Proceedings of the 14th International Conference on Human-computer Interaction with Mobile Devices and Services (MobileHCI '12)*. ACM, New York, NY, USA, 39–48. DOI:http://dx.doi.org/10.1145/2371574.2371582
12. Leo Breiman. 2001. Random Forests. *Machine Learning* 45, 1 (01 Oct 2001), 5–32. DOI: http://dx.doi.org/10.1023/A:1010933404324
13. Christina Bröhl, Alexander Mertens, and Martina Ziefle. 2017. *How Do Users Interact with Mobile Devices? An Analysis of Handheld Positions for Different Technology Generations*. Springer International Publishing, Cham, 3–16. DOI: http://dx.doi.org/10.1007/978-3-319-58536-9_1
14. Frederik Brudy, David Ledo, Saul Greenberg, and Andreas Butz. 2014. Is Anyone Looking? Mitigating Shoulder Surfing on Public Displays Through Awareness and Protection. In *Proceedings of The International Symposium on Pervasive Displays (PerDis '14)*. ACM, New York, NY, USA, Article 1, 6 pages. DOI: http://dx.doi.org/10.1145/2611009.2611028
15. Andreas Bulling. 2016. Pervasive Attentive User Interfaces. *Computer* 49, 1 (Jan. 2016), 94–98. DOI: http://dx.doi.org/10.1109/MC.2016.32
16. Andreas Bulling and Hans Gellersen. 2010. Toward Mobile Eye-Based Human-Computer Interaction. *IEEE Pervasive Computing* 9, 4 (October 2010), 8–12. DOI: http://dx.doi.org/10.1109/MPRV.2010.86
17. Andreas Bulling and Kai Kunze. 2016. Eyewear Computers for Human-computer Interaction. *interactions* 23, 3 (April 2016), 70–73. DOI: http://dx.doi.org/10.1145/2912886
18. Jessica R. Cauchard, Markus Löchtefeld, Pourang Irani, Johannes Schoening, Antonio Krüger, Mike Fraser, and Sriram Subramanian. 2011. Visual Separation in Mobile Multi-display Environments. In *Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology (UIST '11)*. ACM, New York, NY, USA, 451–460. DOI: http://dx.doi.org/10.1145/2047196.2047256
19. Liwei Chan and Kouta Minamizawa. 2017. FrontFace: Facilitating Communication Between HMD Users and Outsiders Using Front-facing-screen HMDs. In *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '17)*. ACM, New York, NY, USA, Article 22, 5 pages. DOI: http://dx.doi.org/10.1145/3098279.3098548
20. Shiwei Cheng. 2011. The Research Framework of Eye-tracking Based Mobile Device Usability Evaluation. In *Proceedings of the 1st International Workshop on Pervasive Eye Tracking & Mobile Eye-based Interaction (PETMEI '11)*. ACM, New York, NY, USA, 21–26. DOI: http://dx.doi.org/10.1145/2029956.2029964
21. T.F. Cootes, C.J. Taylor, D.H. Cooper, and J. Graham. 1995. Active Shape Models-Their Training and Application. *Computer Vision and Image Understanding* 61, 1 (1995), 38 – 59. DOI:http://dx.doi.org/https://doi.org/10.1006/cviu.1995.1004
22. Cira Cuadrat Seix, Montserrat Sendín Veloso, and Juan José Rodríguez Soler. 2012. Towards the Validation of a Method for Quantitative Mobile Usability Testing Based on Desktop Eyetracking. In *Proceedings of the 13th International Conference on InteracciÓN Persona-Ordenador (INTERACCION '12)*. ACM, New York, NY, USA, Article 49, 8 pages. DOI: http://dx.doi.org/10.1145/2379636.2379684
23. Charles Denis and Laurent Karsenty. 2005. *Inter-Usability of Multi-Device Systems - A Conceptual Framework*. John Wiley & Sons, Ltd, 373–385. DOI: http://dx.doi.org/10.1002/0470091703.ch17
24. Connor Dickie, Roel Vertegaal, Changuk Sohn, and Daniel Cheng. 2005. eyeLook: Using Attention to Facilitate Mobile Media Consumption. In *Proceedings of the 18th Annual ACM Symposium on User Interface Software and Technology (UIST '05)*. ACM, New York, NY, USA, 103–106. DOI: http://dx.doi.org/10.1145/1095034.1095050
25. Heiko Drewes, Alexander De Luca, and Albrecht Schmidt. 2007. Eye-gaze Interaction for Mobile Phones. In *Proceedings of the 4th International Conference on Mobile Technology, Applications, and Systems and the 1st International Symposium on Computer Human Interaction in Mobile Technology (Mobility '07)*. ACM, New York, NY, USA, 364–371. DOI: http://dx.doi.org/10.1145/1378063.1378122
26. Heiko Drewes and Albrecht Schmidt. 2007. *Interacting with the Computer Using Gaze Gestures*. Springer Berlin Heidelberg, Berlin, Heidelberg, 475–488. DOI: http://dx.doi.org/10.1007/978-3-540-74800-7_43
27. Andrew T. Duchowski. 2002. A breadth-first survey of eye-tracking applications. *Behavior Research Methods, Instruments, & Computers* 34, 4 (01 Nov 2002), 455–470. DOI:http://dx.doi.org/10.3758/BF03195475
28. Morten Lund Dybdal, Javier San Agustin, and John Paulin Hansen. 2012. Gaze Input for Mobile Devices by Dwell and Gestures. In *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '12)*. ACM, New York, NY, USA, 225–228. DOI: http://dx.doi.org/10.1145/2168556.2168601

29. Maria K. Eckstein, BelÃl'n Guerra-Carrillo, Alison T. Miller Singley, and Silvia A. Bunge. 2017. Beyond eye gaze: What else can eyetracking reveal about cognition and cognitive development? *Developmental Cognitive Neuroscience* 25 (2017), 69 – 91. DOI:http://dx.doi.org/https://doi.org/10.1016/j.dcn.2016.11.001 Sensitive periods across development.

30. Serge Egelman, Sakshi Jain, Rebecca S. Portnoff, Kerwell Liao, Sunny Consolvo, and David Wagner. 2014. Are You Ready to Lock?. In *Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security (CCS '14)*. ACM, New York, NY, USA, 750–761. DOI: http://dx.doi.org/10.1145/2660267.2660273

31. Malin Eiband, Mohamed Khamis, Emanuel von Zezschwitz, Heinrich Hussmann, and Florian Alt. 2017. Understanding Shoulder Surfing in the Wild: Stories from Users and Observers. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 11.

32. Hanene Elleuch, Ali Wali, and Adel M. Alimi. 2014. Smart Tablet Monitoring by a Real-Time Head Movement and Eye Gestures Recognition System. In *2014 International Conference on Future Internet of Things and Cloud*. 393–398. DOI: http://dx.doi.org/10.1109/FiCloud.2014.70

33. Hanene Elleuch, Ali Wali, Anis Samet, and Adel M. Alimi. 2016. *A Real-Time Eye Gesture Recognition System Based on Fuzzy Inference System for Mobile Devices Monitoring*. Springer International Publishing, Cham, 172–180. DOI: http://dx.doi.org/10.1007/978-3-319-48680-2_16

34. Hanene Elleuch, Ali Wali, Anis Samet, and Adel M. Alimi. 2017. Interacting with mobile devices by fusion eye and hand gestures recognition systems based on decision tree approach. (2017). DOI: http://dx.doi.org/10.1117/12.2269010

35. Ioannis Giannopoulos, Peter Kiefer, and Martin Raubal. 2012. GeoGazemarks: Providing Gaze History for the Orientation on Small Display Maps. In *Proceedings of the 14th ACM International Conference on Multimodal Interaction (ICMI '12)*. ACM, New York, NY, USA, 165–172. DOI: http://dx.doi.org/10.1145/2388676.2388711

36. Gaurav Goswami, Mayank Vatsa, and Richa Singh. 2014. RGB-D Face Recognition With Texture and Attribute Features. *Trans. Info. For. Sec.* 9, 10 (Oct. 2014), 1629–1640. DOI: http://dx.doi.org/10.1109/TIFS.2014.2343913

37. Jari Hannuksela, Pekka Sangi, Markus Turtinen, and Janne Heikkilä. 2008. *Face Tracking for Spatially Aware Mobile User Interfaces*. Springer Berlin Heidelberg, Berlin, Heidelberg, 405–412. DOI: http://dx.doi.org/10.1007/978-3-540-69905-7_46

38. Oliver Hohlfeld, André Pomp, Jó Ágila Bitsch Link, and Dennis Guse. 2015. On the Applicability of Computer Vision Based Gaze Tracking in Mobile Scenarios. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '15)*. ACM, New York, NY, USA, 427–434. DOI: http://dx.doi.org/10.1145/2785830.2785869

39. Corey Holland, Atenas Garza, Elena Kurtova, Jose Cruz, and Oleg Komogortsev. 2013. Usability Evaluation of Eye Tracking on an Unmodified Common Tablet. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems (CHI EA '13)*. ACM, New York, NY, USA, 295–300. DOI: http://dx.doi.org/10.1145/2468356.2468409

40. Corey Holland and Oleg Komogortsev. 2012. Eye Tracking on Unmodified Common Tablets: Challenges and Solutions. In *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '12)*. ACM, New York, NY, USA, 277–280. DOI: http://dx.doi.org/10.1145/2168556.2168615

41. Michael Xuelin Huang, Jiajia Li, Grace Ngai, and Hong Va Leong. 2017a. ScreenGlint: Practical, In-situ Gaze Estimation on Smartphones. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 2546–2557. DOI: http://dx.doi.org/10.1145/3025453.3025794

42. Qiong Huang, Ashok Veeraraghavan, and Ashutosh Sabharwal. 2017b. TabletGaze: dataset and analysis for unconstrained appearance-based gaze estimation in mobile tablets. *Machine Vision and Applications* 28, 5 (01 Aug 2017), 445–461. DOI: http://dx.doi.org/10.1007/s00138-017-0852-4

43. Apple Inc. 2018. Use gestures to navigate your iPhone X. website. (30 January 2018). Retrieved February 8, 2018 from https://support.apple.com/en-bn/HT208204.

44. Shoya Ishimaru, Kai Kunze, Yuzuko Utsumi, Masakazu Iwamura, and Koichi Kise. 2013. Where Are You Looking At? - Feature-Based Eye Tracking on Unmodified Tablets. In *2013 2nd IAPR Asian Conference on Pattern Recognition*. 738–739. DOI: http://dx.doi.org/10.1109/ACPR.2013.190

45. Robert J. Jacob and Keith S. Karn. 2003. *Commentary on Section 4. Eye Tracking in Human-Computer Interaction and Usability Research: Ready to Deliver the Promises*. Elsevier, Chapter 26, 573–607.

46. Shahram Jalaliniya and Diako Mardanbegi. 2016. EyeGrip: Detecting Targets in a Series of Uni-directional Moving Objects Using Optokinetic Nystagmus Eye Movements. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 5801–5811. DOI: http://dx.doi.org/10.1145/2858036.2858584

47. Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. 2014. Caffe: Convolutional Architecture for Fast Feature Embedding. In *Proceedings of the 22Nd ACM International Conference on Multimedia (MM '14)*. ACM, New York, NY, USA, 675–678. DOI: http://dx.doi.org/10.1145/2647868.2654889
48. Zhiping Jiang, Jinsong Han, Chen Qian, Wei Xi, Kun Zhao, Han Ding, Shaojie Tang, Jizhong Zhao, and Panlong Yang. 2016. VADS: Visual attention detection with a smartphone. In *IEEE INFOCOM 2016 - The 35th Annual IEEE International Conference on Computer Communications*. 1–9. DOI: http://dx.doi.org/10.1109/INFOCOM.2016.7524398
49. Jari Kangas, Deepak Akkil, Jussi Rantala, Poika Isokoski, Päivi Majaranta, and Roope Raisamo. 2014. Gaze Gestures and Haptic Feedback in Mobile Devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. ACM, New York, NY, USA, 435–438. DOI: http://dx.doi.org/10.1145/2556288.2557040
50. Chiao-Wen Kao, Che-Wei Yang, Kuo-Chin Fan, Bor-Jiunn Hwang, and Chin-Pan Huang. 2011. An adaptive eye gaze tracker system in the integrated cloud computing and mobile device. In *2011 International Conference on Machine Learning and Cybernetics*, Vol. 1. 367–371. DOI: http://dx.doi.org/10.1109/ICMLC.2011.6016686
51. Shinjiro Kawato, Nobuji Tetsutani, and Kenichi Hosaka. 2005. Scale-Adaptive Face Detection and Tracking in Real Time with SSR Filters and Support Vector Machine*This Paper Was Presented at ACCV 2004. *IEICE - Trans. Inf. Syst.* E88-D, 12 (Dec. 2005), 2857–2863. DOI: http://dx.doi.org/10.1093/ietisy/e88-d.12.2857
52. Mohamed Khamis, Florian Alt, Mariam Hassib, Emanuel von Zezschwitz, Regina Hasholzner, and Andreas Bulling. 2016. GazeTouchPass: Multimodal Authentication Using Gaze and Touch on Mobile Devices. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '16)*. ACM, New York, NY, USA, 2156–2164. DOI: http://dx.doi.org/10.1145/2851581.2892314
53. Mohamed Khamis, Anita Baier, Niels Henze, Florian Alt, and Andreas Bulling. 2018a. Understanding Face and Eye Visibility in Front-Facing Cameras of Smartphones used in the Wild. (2018). DOI: http://dx.doi.org/10.1145/3152832.3173854
54. Mohamed Khamis, Daniel Buschek, Tobias Thieron, Florian Alt, and Andreas Bulling. 2018b. EyePACT: Eye-Based Parallax Correction on Touch-Enabled Interactive Displays. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 4, Article 146 (Jan. 2018), 18 pages. DOI: http://dx.doi.org/10.1145/3161168
55. Mohamed Khamis, Regina Hasholzner, Andreas Bulling, and Florian Alt. 2017a. GTmoPass: Two-factor Authentication on Public Displays Using Gaze-touch Passwords and Personal Mobile Devices. In *Proceedings of the 6th ACM International Symposium on Pervasive Displays (PerDis '17)*. ACM, New York, NY, USA, Article 8, 9 pages. DOI: http://dx.doi.org/10.1145/3078810.3078815
56. Mohamed Khamis, Mariam Hassib, Emanuel von Zezschwitz, Andreas Bulling, and Florian Alt. 2017b. GazeTouchPIN: Protecting Sensitive Data on Mobile Devices Using Secure Multimodal Authentication. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction (ICMI 2017)*. ACM, New York, NY, USA, 446–450. DOI: http://dx.doi.org/10.1145/3136755.3136809
57. Mohamed Khamis, Axel Hoesl, Alexander Klimczak, Martin Reiss, Florian Alt, and Andreas Bulling. 2017c. EyeScout: Active Eye Tracking for Position and Movement Independent Gaze Interaction with Large Public Displays. In *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology (UIST '17)*. ACM, New York, NY, USA, 155–166. DOI: http://dx.doi.org/10.1145/3126594.3126630
58. Jaewon Kim, Paul Thomas, Ramesh Sankaranarayana, Tom Gedeon, and Hwan-Jin Yoon. 2015. Eye-tracking analysis of user behavior and performance in web search on large and small screens. *Journal of the Association for Information Science and Technology* 66, 3 (2015), 526–544. DOI: http://dx.doi.org/10.1002/asi.23187
59. Jaewon Kim, Paul Thomas, Ramesh Sankaranarayana, Tom Gedeon, and Hwan-Jin Yoon. 2016a. Pagination Versus Scrolling in Mobile Web Search. In *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management (CIKM '16)*. ACM, New York, NY, USA, 751–760. DOI: http://dx.doi.org/10.1145/2983323.2983720
60. Jaewon Kim, Paul Thomas, Ramesh Sankaranarayana, Tom Gedeon, and Hwan-Jin Yoon. 2016b. Understanding eye movements on mobile devices for better presentation of search results. *Journal of the Association for Information Science and Technology* 67, 11 (2016), 2607–2619. DOI: http://dx.doi.org/10.1002/asi.23628
61. Jaewon Kim, Paul Thomas, Ramesh Sankaranarayana, Tom Gedeon, and Hwan-Jin Yoon. 2017. What Snippet Size is Needed in Mobile Web Search?. In *Proceedings of the 2017 Conference on Conference Human Information Interaction and Retrieval (CHIIR '17)*. ACM, New York, NY, USA, 97–106. DOI: http://dx.doi.org/10.1145/3020165.3020173
62. Dominik Kirst and Andreas Bulling. 2016. On the Verge: Voluntary Convergences for Accurate and Precise Timing of Gaze Input. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '16)*. ACM, New York, NY, USA, 1519–1525. DOI: http://dx.doi.org/10.1145/2851581.2892307

63. Jesper Kjeldskov and Jeni Paay. 2012. A Longitudinal Review of Mobile HCI Research Methods. In *Proceedings of the 14th International Conference on Human-computer Interaction with Mobile Devices and Services (MobileHCI '12)*. ACM, New York, NY, USA, 69–78. DOI:http://dx.doi.org/10.1145/2371574.2371586

64. Jesper Kjeldskov and Mikael B. Skov. 2014. Was It Worth the Hassle?: Ten Years of Mobile HCI Research Discussions on Lab and Field Evaluations. In *Proceedings of the 16th International Conference on Human-computer Interaction with Mobile Devices & Services (MobileHCI '14)*. ACM, New York, NY, USA, 43–52. DOI:http://dx.doi.org/10.1145/2628363.2628398

65. Thomas Kosch, Mariam Hassib, Pawel Wozniak, Daniel Buschek, and Florian Alt. 2018. Your Eyes Tell: L everaging Smooth Pursuit for Assessing Cognitive Workload. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA. DOI: http://dx.doi.org/10.1145/3173574.3174010

66. Kyle Krafka, Aditya Khosla, Petr Kellnhofer, Harini Kannan, Suchendra Bhandarkar, Wojciech Matusik, and Antonio Torralba. 2016. Eye Tracking for Everyone. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2176–2184. DOI: http://dx.doi.org/10.1109/CVPR.2016.239

67. Kai Kunze, Shoya Ishimaru, Yuzuko Utsumi, and Koichi Kise. 2013. My Reading Life: Towards Utilizing Eyetracking on Unmodified Tablets and Phones. In *Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication (UbiComp '13 Adjunct)*. ACM, New York, NY, USA, 283–286. DOI: http://dx.doi.org/10.1145/2494091.2494179

68. Christian Lander, Felix Kosmalla, Frederik Wiehr, and Sven Gehring. 2017. Using Corneal Imaging for Measuring a Human's Visual Attention. In *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers (UbiComp '17)*. ACM, New York, NY, USA, 947–952. DOI: http://dx.doi.org/10.1145/3123024.3124563

69. David Lee, KyoungHee Son, Joon Hyub Lee, and Seok-Hyung Bae. 2012. PhantomPen: Virtualization of Pen Head for Digital Drawing Free from Pen Occlusion & Visual Parallax. In *Proceedings of the 25th Annual ACM Symposium on User Interface Software and Technology (UIST '12)*. ACM, New York, NY, USA, 331–340. DOI: http://dx.doi.org/10.1145/2380116.2380159

70. Jong-In Lee, Sunjun Kim, Masaaki Fukumoto, and Byungjoo Lee. 2017. Reflector: Distance-Independent, Private Pointing on a Reflective Screen. In *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology (UIST '17)*. ACM, New York, NY, USA, 351–364. DOI: http://dx.doi.org/10.1145/3126594.3126665

71. Vincent Lepetit, Francesc Moreno-Noguer, and Pascal Fua. 2008. EPnP: An Accurate O(n) Solution to the PnP Problem. *International Journal of Computer Vision* 81, 2 (19 Jul 2008), 155. DOI: http://dx.doi.org/10.1007/s11263-008-0152-6

72. Yinghui Li, Zhichao Cao, and Jiliang Wang. 2017a. Gazture: Design and Implementation of a Gaze Based Gesture Control System on Tablets. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 74 (Sept. 2017), 17 pages. DOI:http://dx.doi.org/10.1145/3130939

73. Zhenjiang Li, Mo Li, Prasant Mohapatra, Jinsong Han, and Shuaiyu Chen. 2017b. iType: Using eye gaze to enhance typing privacy. In *IEEE INFOCOM 2017 - IEEE Conference on Computer Communications*. 1–9. DOI: http://dx.doi.org/10.1109/INFOCOM.2017.8057233

74. Dachuan Liu, Bo Dong, Xing Gao, and Haining Wang. 2015. *Exploiting Eye Tracking for Smartphone Authentication*. Springer International Publishing, Cham, 457–477. DOI: http://dx.doi.org/10.1007/978-3-319-28166-7_22

75. Kristian Lukander. 2004. Measuring Gaze Point on Handheld Mobile Devices. In *CHI '04 Extended Abstracts on Human Factors in Computing Systems (CHI EA '04)*. ACM, New York, NY, USA, 1556–1556. DOI: http://dx.doi.org/10.1145/985921.986132

76. Christian Mai, Lukas Rambold, and Mohamed Khamis. 2017. TransparentHMD: Revealing the HMD User's Face to Bystanders. In *Proceedings of the 16th International Conference on Mobile and Ubiquitous Multimedia (MUM '17)*. ACM, New York, NY, USA, 515–520. DOI: http://dx.doi.org/10.1145/3152832.3157813

77. Päivi Majaranta and Andreas Bulling. 2014. *Eye Tracking and Eye-Based Human-Computer Interaction*. Springer London, 39–65. DOI: http://dx.doi.org/10.1007/978-1-4471-6392-3_3

78. Subhransu Maji, Alexander C. Berg, and Jitendra Malik. 2008. Classification using intersection kernel support vector machines is efficient. In *2008 IEEE Conference on Computer Vision and Pattern Recognition*. 1–8. DOI: http://dx.doi.org/10.1109/CVPR.2008.4587630

79. Khalid Majrashi, Margaret Hamilton, and Alexandra L. Uitdenbogerd. 2014. Cross-platform Usability and Eye-tracking Measurement and Analysis Model. In *Proceedings of the 26th Australian Computer-Human Interaction Conference on Designing Futures: The Future of Design (OzCHI '14)*. ACM, New York, NY, USA, 418–421. DOI: http://dx.doi.org/10.1145/2686612.2686677

80. Khalid Majrashi, Margaret Hamilton, and Alexandra L. Uitdenbogerd. 2016. Correlating Cross-platform Usability Problems with Eye Tracking Patterns. In *Proceedings of the 30th International BCS Human Computer Interaction Conference: Fusion! (HCI '16)*.

BCS Learning & Development Ltd., Swindon, UK, Article 40, 11 pages. DOI: http://dx.doi.org/10.14236/ewic/HCI2016.40

81. Diako Mardanbegi, Dan Witzner Hansen, and Thomas Pederson. 2012. Eye-based Head Gestures. In *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '12)*. ACM, New York, NY, USA, 139–146. DOI: http://dx.doi.org/10.1145/2168556.2168578

82. Alex Mariakakis, Jacob Baudin, Eric Whitmire, Vardhman Mehta, Megan A. Banks, Anthony Law, Lynn Mcgrath, and Shwetak N. Patel. 2017. PupilScreen: Using Smartphones to Assess Traumatic Brain Injury. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 81 (Sept. 2017), 27 pages. DOI: http://dx.doi.org/10.1145/3131896

83. Alexander Mariakakis, Mayank Goel, Md Tanvir Islam Aumi, Shwetak N. Patel, and Jacob O. Wobbrock. 2015. SwitchBack: Using Focus and Saccade Tracking to Guide Users' Attention for Mobile Task Resumption. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. ACM, New York, NY, USA, 2953–2962. DOI: http://dx.doi.org/10.1145/2702123.2702539

84. Emiliano Miluzzo, Tianyu Wang, and Andrew T. Campbell. 2010. EyePhone: Activating Mobile Phones with Your Eyes. In *Proceedings of the Second ACM SIGCOMM Workshop on Networking, Systems, and Applications on Mobile Handhelds (MobiHeld '10)*. ACM, New York, NY, USA, 15–20. DOI: http://dx.doi.org/10.1145/1851322.1851328

85. Takashi Nagamatsu, Michiya Yamamoto, and Hiroshi Sato. 2010. MobiGaze: Development of a Gaze Interface for Handheld Mobile Devices. In *CHI '10 Extended Abstracts on Human Factors in Computing Systems (CHI EA '10)*. ACM, New York, NY, USA, 3349–3354. DOI: http://dx.doi.org/10.1145/1753846.1753983

86. Gustav Öquist and Kristin Lundin. 2007. Eye Movement Study of Reading Text on a Mobile Phone Using Paging, Scrolling, Leading, and RSVP. In *Proceedings of the 6th International Conference on Mobile and Ubiquitous Multimedia (MUM '07)*. ACM, New York, NY, USA, 176–183. DOI: http://dx.doi.org/10.1145/1329469.1329493

87. Lucas Paletta, Helmut Neuschmied, Michael Schwarz, Gerald Lodron, Martin Pszeida, Stefan Ladstätter, and Patrick Luley. 2014. Smartphone Eye Tracking Toolbox: Accurate Gaze Recovery on Mobile Displays. In *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '14)*. ACM, New York, NY, USA, 367–68. DOI: http://dx.doi.org/10.1145/2578153.2628813

88. Lucas Paletta, Stephanie Schwarz, Jan Bobeth, Michael Schwarz, and Manfred Tscheligi. 2015. Gaze Analysis in Mobile Pedestrians Navigation: Socio-Cultural Aspects and Wayfinding. In *Proceedings of the 2nd International Workshop on Solutions for Automatic Gaze Data Analysis*. DOI:http://dx.doi.org/10.2390/biecoll-saga2015

89. Thies Pfeiffer, Marc Erich Latoschik, and Ipke Wachsmuth. 2008. Evaluation of binocular eye trackers and algorithms for 3D gaze interaction in virtual reality environments. *JVRB - Journal of Virtual Reality and Broadcasting* 5, 16 (2008), 1660.

90. Ken Pfeuffer and Hans Gellersen. 2016. Gaze and Touch Interaction on Tablets. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology (UIST '16)*. ACM, New York, NY, USA, 301–311. DOI: http://dx.doi.org/10.1145/2984511.2984514

91. Bastian Pfleging, Drea K. Fekety, Albrecht Schmidt, and Andrew L. Kun. 2016. A Model Relating Pupil Diameter to Mental Workload and Lighting Conditions. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 5776–5788. DOI: http://dx.doi.org/10.1145/2858036.2858117

92. Carmelo Pino and Isaak Kavasidis. 2012. Improving mobile device interaction by eye tracking analysis. In *2012 Federated Conference on Computer Science and Information Systems (FedCSIS)*. 1199–1202.

93. Thammathip Piumsomboon, Gun Lee, Robert W. Lindeman, and Mark Billinghurst. 2017. Exploring natural eye-gaze-based interaction for immersive virtual reality. In *2017 IEEE Symposium on 3D User Interfaces (3DUI)*. 36–39. DOI: http://dx.doi.org/10.1109/3DUI.2017.7893315

94. Pardha S. Pyla, Manas Tungare, Jerome Holman, and Manuel A. Pérez-Quiñones. 2009. *Continuous User Interfaces for Seamless Task Migration*. Springer Berlin Heidelberg, Berlin, Heidelberg, 77–85. DOI: http://dx.doi.org/10.1007/978-3-642-02580-8_9

95. Qing-Xing Qu, Le Zhang, Wen-Yu Chao, and Vincent Duffy. 2017. *User Experience Design Based on Eye-Tracking Technology: A Case Study on Smartphone APPs*. Springer International Publishing, Cham, 303–315. DOI:http://dx.doi.org/10.1007/978-3-319-41627-4_27

96. Jussi Rantala, PÃď'ivi Majaranta, Jari Kangas, Poika Isokoski, Deepak Akkil, Oleg Åăpakov, and Roope Raisamo. 2017. Gaze Interaction With Vibrotactile Feedback: Review and Design Guidelines. *Human-Computer Interaction* 0, 0 (2017), 1–39. DOI: http://dx.doi.org/10.1080/07370024.2017.1306444

97. Milena Roetting and Olaf Zukunft. 2014. Don't touch that tablet: An evaluation of gaze-based interfaces for tablet computers. In *6th International Conference on Mobile Computing, Applications and Services*. 49–56. DOI: http://dx.doi.org/10.4108/icst.mobicase.2014.257760

98. D. Rozado, T. Moreno, J. San Agustin, F. B. Rodriguez, and P. Varona. 2015. Controlling a Smartphone Using Gaze Gestures As the Input Mechanism. *Hum.-Comput. Interact.* 30, 1 (Jan. 2015), 34–63. DOI: http://dx.doi.org/10.1080/07370024.2013.870385

99. Matthias Seeger. 2004. Gaussian Processes for Machine Learning. *International Journal of Neural Systems* 14, 02 (2004), 69–106. DOI: http://dx.doi.org/10.1142/S0129065704001899 PMID: 15112367.

100. Brian A. Smith, Qi Yin, Steven K. Feiner, and Shree K. Nayar. 2013. Gaze Locking: Passive Eye Contact Detection for Human-object Interaction. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology (UIST '13)*. ACM, New York, NY, USA, 271–280. DOI: http://dx.doi.org/10.1145/2501988.2501994

101. Chen Song, Aosen Wang, Kui Ren, and Wenyao Xu. 2016. "EyeVeri: A Secure and Usable Approach for Smartphone User Authentication". In *IEEE International Conference on Computer Communication (INFOCOM'16)*. San Francisco, California, 1 – 9.

102. Yusuke Sugano, Yasuyuki Matsushita, and Yoichi Sato. 2014. Learning-by-Synthesis for Appearance-Based 3D Gaze Estimation. In *2014 IEEE Conference on Computer Vision and Pattern Recognition*. 1821–1828. DOI: http://dx.doi.org/10.1109/CVPR.2014.235

103. Yusuke Sugano, Xucong Zhang, and Andreas Bulling. 2016. AggreGaze: Collective Estimation of Audience Attention on Public Displays. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology (UIST '16)*. ACM, New York, NY, USA, 821–831. DOI: http://dx.doi.org/10.1145/2984511.2984536

104. Po-He Tseng, Ian G. M. Cameron, Giovanna Pari, James N. Reynolds, Douglas P. Munoz, and Laurent Itti. 2013. High-throughput classification of clinical populations from natural viewing eye movements. *Journal of Neurology* 260, 1 (01 Jan 2013), 275–284. DOI:http://dx.doi.org/10.1007/s00415-012-6631-2

105. Jayson Turner, Jason Alexander, Andreas Bulling, Dominik Schmidt, and Hans Gellersen. 2013a. Eye Pull, Eye Push: Moving Objects between Large Screens and Personal Devices with Gaze and Touch. In *Human-Computer Interaction – INTERACT 2013*. Lecture Notes in Computer Science, Vol. 8118. Springer Berlin Heidelberg, 170–186. DOI: http://dx.doi.org/10.1007/978-3-642-40480-1_11

106. Jayson Turner, Andreas Bulling, Jason Alexander, and Hans Gellersen. 2013b. Eye Drop: An Interaction Concept for Gaze-supported Point-to-point Content Transfer. In *Proceedings of the 12th International Conference on Mobile and Ubiquitous Multimedia (MUM '13)*. ACM, New York, NY, USA, Article 37, 4 pages. DOI:http://dx.doi.org/10.1145/2541831.2541868

107. Jayson Turner, Andreas Bulling, Jason Alexander, and Hans Gellersen. 2014. Cross-device Gaze-supported Point-to-point Content Transfer. In *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '14)*. ACM, New York, NY, USA, 19–26. DOI: http://dx.doi.org/10.1145/2578153.2578155

108. Vytautas Vaitukaitis and Andreas Bulling. 2012. Eye Gesture Recognition on Portable Devices. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing (UbiComp '12)*. ACM, New York, NY, USA, 711–714. DOI:http://dx.doi.org/10.1145/2370216.2370370

109. Davide Valeriani and Ana Matran-Fernandez. 2015. Towards a wearable device for controlling a smartphone with eye winks. In *2015 7th Computer Science and Electronic Engineering Conference (CEEC)*. 41–46. DOI: http://dx.doi.org/10.1109/CEEC.2015.7332697

110. Roel Vertegaal. 2003. Attentive user interfaces. *Commun. ACM* 46, 3 (2003), 30–33.

111. Roel Vertegaal, Connor Dickie, Changuk Sohn, and Myron Flickner. 2002. Designing Attentive Cell Phone Using Wearable Eyecontact Sensors. In *CHI '02 Extended Abstracts on Human Factors in Computing Systems (CHI EA '02)*. ACM, New York, NY, USA, 646–647. DOI:http://dx.doi.org/10.1145/506443.506526

112. Vladimir Vezhnevets and Anna Degtiareva. 2003. Robust and accurate eye contour extraction. In *Graphicon*.

113. Mélodie Vidal, Andreas Bulling, and Hans Gellersen. 2013. Pursuits: Spontaneous Interaction with Displays Based on Smooth Pursuit Eye Movement and Moving Targets. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '13)*. ACM, New York, NY, USA, 439–448. DOI:http://dx.doi.org/10.1145/2493432.2493477

114. Paul Viola and Michael J. Jones. 2004. Robust Real-Time Face Detection. *International Journal of Computer Vision* 57, 2 (2004), 137–154. DOI: http://dx.doi.org/10.1023/B:VISI.0000013087.49260.fb

115. Raphael Wimmer. 2011. Grasp Sensing for Human-computer Interaction. In *Proceedings of the Fifth International Conference on Tangible, Embedded, and Embodied Interaction (TEI '11)*. ACM, New York, NY, USA, 221–228. DOI: http://dx.doi.org/10.1145/1935701.1935745

116. Erroll Wood, Tadas Baltruaitis, Xucong Zhang, Yusuke Sugano, Peter Robinson, and Andreas Bulling. 2015. Rendering of Eyes for Eye-Shape Registration and Gaze Estimation. In *Proceedings of the 2015 IEEE International Conference on Computer Vision (ICCV) (ICCV '15)*. IEEE Computer Society, Washington, DC, USA, 3756–3764. DOI: http://dx.doi.org/10.1109/ICCV.2015.428

117. Erroll Wood and Andreas Bulling. 2014. EyeTab: Model-based Gaze Estimation on Unmodified Tablet Computers. In *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '14)*. ACM, New York, NY, USA, 207–210. DOI: http://dx.doi.org/10.1145/2578153.2578185

118. Xuehan Xiong, Zicheng Liu, Qin Cai, and Zhengyou Zhang. 2014. Eye Gaze Tracking Using an RGBD Camera: A Comparison with a RGB Solution. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication (UbiComp '14 Adjunct)*. ACM, New York, NY, USA, 1113–1121. DOI: http://dx.doi.org/10.1145/2638728.2641694

119. Xiaoyi Zhang, Harish Kulkarni, and Meredith Ringel Morris. 2017. Smartphone-Based Gaze Gesture Communication for People with Motor Disabilities. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 2878–2889. DOI: http://dx.doi.org/10.1145/3025453.3025790

120. Xucong Zhang, Yusuke Sugano, Mario Fritz, and Andreas Bulling. 2017. It's Written All Over Your Face: Full-Face Appearance-Based Gaze Estimation. In *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*. 2299–2308. DOI: http://dx.doi.org/10.1109/CVPRW.2017.284

121. Yanxia Zhang, Andreas Bulling, and Hans Gellersen. 2013. SideWays: A Gaze Interface for Spontaneous Interaction with Situated Displays. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 851–860. DOI: http://dx.doi.org/10.1145/2470654.2470775

122. Yanxia Zhang, Jörg Müller, Ming Ki Chong, Andreas Bulling, and Hans Gellersen. 2014. GazeHorizon: Enabling Passers-by to Interact with Public Displays by Gaze. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '14)*. ACM, New York, NY, USA, 559–563. DOI: http://dx.doi.org/10.1145/2632048.2636071

123. Huiyuan Zhou, Vinicius Ferreira, Thamara Alves, Kirstie Hawkey, and Derek Reilly. 2015. Somebody Is Peeking!: A Proximity and Privacy Aware Tablet Interface. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '15)*. ACM, New York, NY, USA, 1971–1976. DOI: http://dx.doi.org/10.1145/2702613.2732726

124. Qiushi Zhou and Eduardo Velloso. 2017. GazeGrip: Improving Mobile Device Accessibility with Gaze & Grip Interaction. In *Proceedings of the 29th Australian Conference on Computer-Human Interaction (OZCHI '17)*. ACM, New York, NY, USA, 467–471. DOI: http://dx.doi.org/10.1145/3152771.3156159