Upright or Sideways? Analysis of Smartphone Postures in the Wild

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ABSTRACT
In this paper, we investigate how smartphone applications, in particular web browsers, are used on mobile phones. Using a publicly available widget for smart phones, we recorded app usage and the phones' acceleration and orientation from 1,330 devices. Combining app usage and sensor data we derive the device's typical posture while different apps are used. Analyzing motion data shows that devices are moved more while messaging and navigation apps are used as opposed to browser and other common applications. The time distribution between landscape and portrait depicts that most of the landscape mode time is used for burst interaction (e.g., text entry), except for Media apps, which are mostly used in landscape mode. Additionally, we found that over 31% of our users use more than one web browser. Our analysis reveals that the duration of mobile browser sessions is longer by a factor of 1.5 when browsers are explicitly started through the system's launcher in comparison to being launched from within another app. Further, users switch back and forth between apps and web browsers, which suggest that a tight and smooth integration of web browsers with native apps can improve the overall usability. From our findings we derive design guidelines for app developers.

ACM Classification Keywords
H5.2 [Information interfaces and presentation]: User Interfaces. - Graphical user interfaces.

Author Keywords
posture, orientation, device motion, WWW, web browser, mobile phone, surfing, accelerometer, session

INTRODUCTION
Over the last decade, mobile phones have become the most ubiquitous devices. There were, for example, over 1.2 billion mobile web users in 2012 [21]. A large body of work investigates how these devices are used in daily life. Previous work mainly focused on controlled studies that draw a rich picture but only of a few participants. Another direction uses surveys and analyzes log files to provide a general overview but cannot provide a detailed picture. In contrast, we collect sensor data from a large number of devices to provide insight about mobile users' behavior on a global scale. In this paper we focus on analyzing how mobile phones are held and moved while common apps and in particular web browsers are used.

Early research by Oulasvirta et al. shows the importance to conduct in-situ experiments when analyzing mobile usage behavior [24]. They discuss how attention span dramatically drops when comparing controlled interactions in the laboratory with interactions in mobile situations. Additionally, user interactions with smartphones considerably vary depending on the user and the apps used. Following a similar direction, our goal is to learn about how apps and in particular web browsers are used on mobile phones. In contrast to previous work, we take into account sensor data recorded by smartphones. Therefore, we built a widget for the Android platform that monitors the currently running app and collects data from the phones' 3D accelerometer sensor. We measure how the smartphone is accelerated whenever the user interacts with it while using various apps. Analyzing this data, we can derive how the phone is held and moved while representative apps are used. Further, we are able to determine the app that is used before another app is started. This provides us with insights of usage behavior with apps on phones. The work described here is, to the best of our knowledge, the first attempt to augment app usage behavior with sensor data to assess postures of mobile phones in the wild.

In this paper we provide the following contributions:

1. We show that phones are being moved more during usage of navigation and messaging applications. Further, the mobile device is being moved about less when web browsers are used in comparison with other apps such as Gmail, SMS, and Google Maps.
2. We confirm that most apps including web browsers are mainly used in portrait mode. However, users briefly rotate the phone into landscape mode, for example, to read or enter text. On the other hand, Media apps are mainly used in landscape mode.
3. Using another web browser in addition to the Android default web browser is common.
4. The duration of web browsing sessions varies depending on apps used right before launching the web browser.

Based on these findings we provide initial recommendations for developers.

The paper is organized as follows: first, we discuss related work followed by an introduction of the widget we implemented for the study. Second, we describe the data set we

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recorded during our investigation. We report the device orientation in general and during a user session while using various apps including web browsers. Furthermore, we analyze the duration of web surfing sessions on mobile phones, followed by a discussion of implications and limitations. Finally, we conclude our findings and describe possible future work.

RELATED WORK

Studying user behavior in real life situations can reveal valuable insights that differ vastly from the insights gained from lab studies [17, 24]. Froehlich et al. [7], for example, developed a system that captured objective and subjective data about mobile computing activities. In two small scale studies the authors describe that the system can help to understand how people use and experience mobile technology. Similarly, Demieux and Losguin designed a framework to collect objective usage data to incorporate the findings into the design process and conducted a field trial with eleven participants [6]. Verkasalo showed that users use certain types of mobile services in certain contexts [34]. The phone was used only 27 % while being on the move. He further reports that users mostly use browsers and multimedia services when they are on the move but play more games while being at home.

How people use the mobile Internet has been the focus of a large body of work. The context of the mobile Internet use is classified in two ways [16, 18]: (1) *Personal context* is the state or condition of the user, e.g., mental goals and body positions, (2) *Environmental context* is a set of outer circumstances, e.g., the presence of other people. Through a diary study it is concluded that users usually use mobile Internet with one hand in a static position indoors. Taylor et al. assessed motivations of mobile Internet users [32]. The most frequent motivation among mobile web users is awareness, a motivation usually satisfied with status checking behavior. They characterize participants and provide suggestions for further development. User experience factors in the mobile web is also addressed in a framework proposed in [26]. Tossell et al. conducted a one year long field trial with 24 iPhone users and analyzed the web usage on smartphones [33]. They characterize their participants and provide directions for further development. Cui and Roto investigated how people use the mobile web via contextual inquiries [5]. They find that the time-frame of web sessions is short in general, but browser usage is longer if users are connected to WLAN.

Researchers have particularly assessed how search engines are used on mobile devices. Church et al., for example, reported that queries are short and users tend to focus on the first few search results. Vojnovic focused on temporal dynamics, semantics, and topics of queries [35]. He reports that 80% of the users issue only a single query per week and queries are executed in bursts. Kamvar et al. compared search patterns across desktop computers, iPhones, and conventional mobile phones [15]. They report that for higher-end phones, a close integration with the standard computer¡ interface would be beneficial for the user since these phones seem to be treated as an extension of the users' computer. Church and Oliver compared mobile web access patterns in 2011 with previous findings by conducting a 4-week diary and interview study [4]. They report the popularity of stationary mobile web access is increasing, i.e., at home or at work. Further, they found a preference for native mobile applications as opposed to general web browsing.

Most work that investigates mobile Internet usage or mobile device usage in general is based on a rather small number of participants with often similar backgrounds. As this can hinder generalizations, researchers recently proposed to use mobile application stores as means to conduct human subject studies [11, 12]. This approach has been used to investigate diverse questions. Henze et al., for example, used mobile games published in a mobile application store to assess touch performance [13] and typing behavior on mobile devices [14]. Non-verbal communication using mobile apps has also been assessed by publishing an app in a marketplace [28, 30]. McMillan et al. describe that this approach can even be used to collect subjective feedback on a large scale [20]. *AppAware* allows its users to see what applications are being installed around their position. The app is used to learn which apps users install [8] install on their device. Böhmer et al. conducted a large-scale study to monitor application usage from smartphones [2]. They report basic and contextual descriptive statics. Based on the information a recommendation system called *Appazaar* is developed [1]. Leiva et al. took the research question Oulasvirta et al. investigated in a controlled setting [24] to the wild [19]. They show that interruptions while using apps are caused by intentionally switching back and forth between applications or unintentionally by incoming phone calls. They report that these interruptions rarely happen but may introduce significant overhead.

Previous work on mobile device usage focuses mainly on studies with few and often highly specific users. The results can provide a very rich picture but cannot always be generalized. In contrast, large-scale studies of mobile device usage investigate either specific applications or focus on when and for how long mobile apps are used. In contrast, we are interested in how users hold their mobile phone while using apps and surfing the Web. We collect a large corpus that combines the application usage with the basic sensors' data current smartphones offer. Thereby, we can derive the posture and movement of the mobile phone while different apps are being used.

DATA ACQUISITION

To understand how users hold and move their devices while using different apps and browsing the Web, we developed a widget for the Android platform (Figure 1). It is compatible with Android 2.3 and higher versions. The widget is a quick start bar which can be added to the phone's home screen. It allows users to quickly launch apps most frequently used. Once a user installs and places the widget on the home screen, the widget monitors the apps used on the phone. The widget determines and logs the current foreground app every second (1 Hz) using the standard Android API. Thereby, we can detect when a new app is started and the previous app is sent to the background. Each time an app is removed from the foreground, the app's identifier, the start time, and the end time is saved to an internal database on the phone. Therefore, we

Figure 1. Screenshots of the widget's one-row layout (left), the two-row layout (center), and a list to hide apps (right). The widget also collects accelerometer data.

know how long an app is being used as well as the sequence of apps used on the phone. The widget uses this information to show the icons and names of the apps most frequently accessed. It offers two different layouts. A layout with one row shows the five most frequent apps (Figure 1.left) and a layout with two rows shows ten apps (Figure 1.center). Tapping an app's icon shown by the widget launches the respective app. The widget has a semi-transparent white background that separates it from the rest of the home screen. A setting menu allows users to choose which apps should be displayed by the widget (see Figure 1.right).

While collecting information about the apps currently used, the widget also records sensor data. It collects the three axes of the acceleration sensor and the three orientation axes provided by a virtual orientation sensor. Data from both sensors is recorded with the fastest rate offered by the respective phone (e.g., 50 Hz for the Samsung Nexus S phone). In addition, the widget monitors when the display is turned on and off. We do not record any data while the display is turned off. Every two minutes and when the display is turned off, all collected data is transmitted to our server. If the transmission fails, the data is re-transmitted the next time a transmission is scheduled.

Publishing the Widget

We distributed the widget through Google Play, the Google store for Android apps to record data from a large and diverse sample. We released the first version of the widget in August 2011. The app's description in the market informed users about collecting the data. We did not advertise the widget among our peers and colleagues to avoid biasing the user. Based on information from the market, the widget received a 3.8 rating on the 5-point scale (five is the maximum rating) and 55 comments. Most of the comments are positive. Negative comments mainly request more features (e.g., more layout options) or criticize the increase of battery consumption and the data traffic caused. The initial version of the widget only monitored the apps used without recording sensor data. We released several updates to improve its usability before integrating the recording of sensor data. All data considered in the following was collected from users who installed or updated the widget between mid-June of 2012 and beginning of September 2012.

Locale	# Devices	Percentages
Japan	447	33.61%
US	309	23.23%
Germany	159	11.95%
UK	123	9.25%

Table 1. The four most common locales in the data set.

Dataset

We collected data from 1,330 unique devices that each provided more than 60 minutes of sensor data. The devices and locales we observed are diverse. In total, we collected data from 307 different device models. The data set covers the typical spectrum of Android phones, including older devices like the Samsung Galaxy S (1.43%, 19 devices) and large high-end device such as the Samsung Galaxy Note (4.13%, 55 devices). The Samsung Galaxy II is the most common phone in our data set (7.14%, 95 devices). Users with 72 different locales used the widget. Table 1 includes the four most common locales.

We observed the usage of 14,471 different apps. The majority of these apps, however, were only used on a small number of devices for a short time. Totally, 13,904 apps were used on less than 10 different devices or for less than 60 minutes. The remaining 567 apps account for 72.37% of the data. For a robust analysis we considered apps that were frequently used by a number of users and represented different categories of apps. Hence, we chose twelve popular apps from six different categories for further analysis (21.01% of the data). We selected the two most frequently apps used in each category to avoid the results being solely based on a specific app. Table 2 shows the selected apps and their categories. We intentionally excluded games for our analysis due to the fact that some games use the accelerometer as an interaction modality. Furthermore, there are very few games that were played across many users in our data set.

DEVICE ORIENTATION

In the first step we analyzed the devices' posture while using various apps derived from the accelerometer data. We measured the duration the devices were held with a partic-

App	Devices	Duration	Category
YouTube	474	16.0 days	Media
Android Video Player	176	2.5 days	
Facebook	717	38.2 days	Social
Twitter	184	5.3 days	
GMail	786	11.1 days	Mail
Android Email Client	337	3.5 days	
Android Browser	1084	54.9 days	Browser
Chrome	223	10.0 days	
SMS	741	20.5 days	Messaging
WhatsApp	295	24.0 days	
Google Maps	687	13.8 days	Navigation
Waze	30	3.6 days	

Table 2. The 12 popular apps from 6 categories we consider for our analysis. The table shows the number of devices that used the apps, the amount of sensor data, and the apps' category.

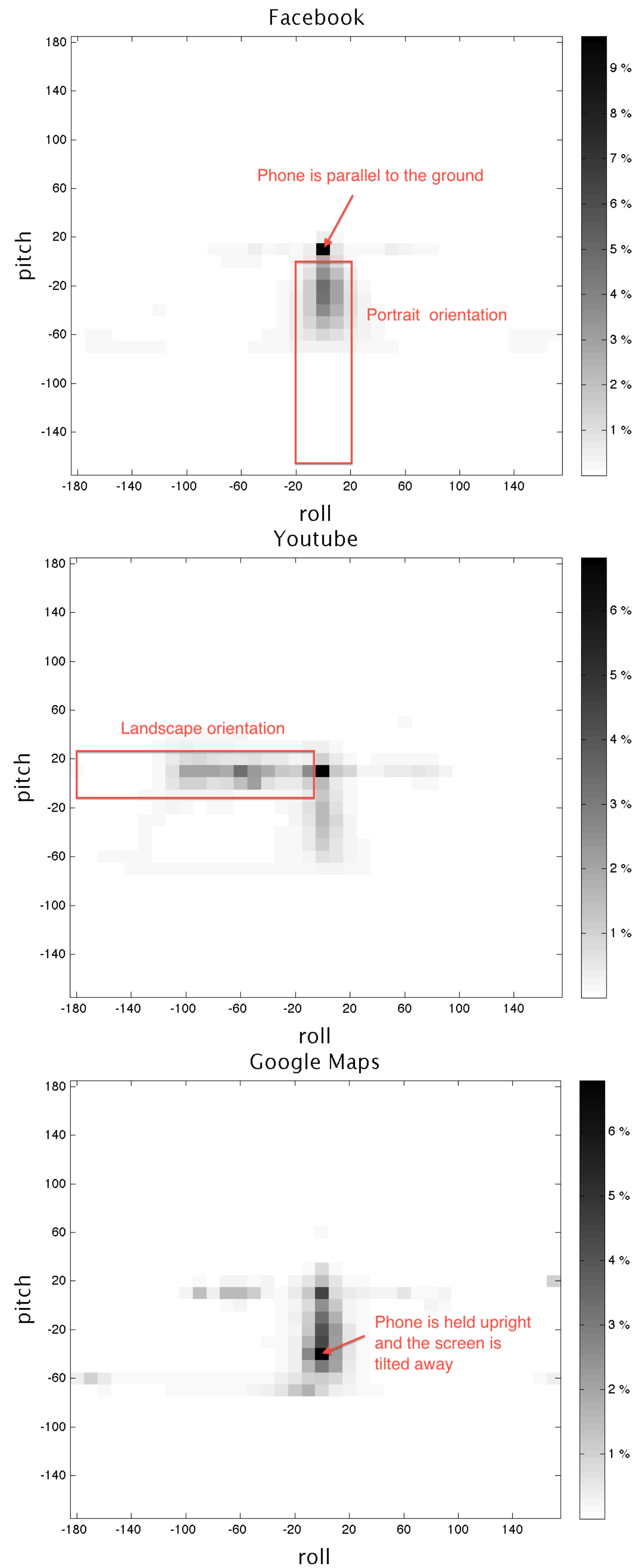

Figure 2. The 2D histograms of the devices' orientation while using Facebook, YouTube, and Google maps. The devices' average pitch and roll are computed over 0.5s windows and binned using 10° intervals.

ular roll and pitch. We binned the orientation in 10° intervals, resulting in 36x36 bins. Figure 2 depicts the heat maps for three apps: *Facebook*, *YouTube*, and *Google Maps*. Assessing this information for a variety of apps reveals that the phones' orientation differs significantly while using different apps. Looking at Figure 2, the heat maps are fairly unique for each application. However, they also share some similarities. The *Facebook*, *YouTube* apps have a peak around 0/0. The peak shows devices lying on a flat surface or being held in parallel to the ground. The peak for the *Google Maps* shows that the device is mainly held upright and the top of the phone is tilted away from the user. We also found that there are often little movements while devices have these orientations. Furthermore, high values are concentrated along the two axes. For *Facebook*, for example, the device is almost exclusively oriented upright and the top of the screen is tilted away from the user. For *YouTube* high values are also concentrated along the second axis indicating that the device is also oriented sideways.

We further assessed how much the phones moved while using various apps. We calculated the standard deviation (SD) of the acceleration vectors' magnitude using 0.5s windows. This value reveals the devices motion. The higher the value, the more movement the device recorded. The movement can be either due to the device movement or the interaction with the device. Figure 3 shows the SD for the 12 apps. Interestingly, these values significantly differ between the categories. Using the devices' average SD, we conducted a one-way ANOVA to statistically compare the device motion between the apps. The results show that the app significantly affected the average SD, $F(11, 5{,}130)=25.32$, $p<.001$. Due to the different sample sizes we used Hochberg's GT2 post hoc test [31]. The two navigation apps have a significantly higher SDs than all other apps (all $p<.01$ or $p<.001$) except the two messaging apps. Both messaging apps have a significantly higher SD than the *Browser* ($p<.001$), *Facebook* ($p<.001$), and *Google Mail* (*WhatsApp* $p<.05$, SMS $p<.001$). The *SMS* app also has a higher SD than Twitter ($p<.01$). Finally, the *Browser* has a lower SD than *YouTube* and the mail apps (all $p<.01$).

Overall, based on the average motion the apps can be grouped in at least three categories (navigation, messaging, and the rest). It is not overly surprising that the phone is being moved more while using navigation apps. However, the difference between messaging and other apps suggests that they are also more often used while on the go.

Orientation Spectrum in a Session

We further analyzed the user interface (UI) orientation while the apps are used. The Android system can automatically rotate the UI depending on the phone's orientation. We analyzed the sensor data to determine whether the UI was displayed in portrait or landscape mode. We used the original code from the Android repository that is used to determine the orientation mode on actual devices and feed it with our accelerometer data. Thereby, we determined the active orientation as well as transitions from landscape to portrait and vice versa. We investigated the UI orientation mode during

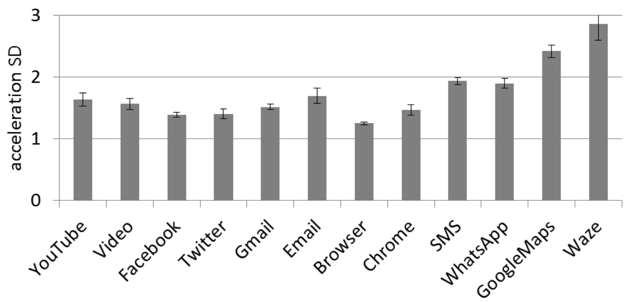

Figure 3. The average standard deviation of the acceleration vectors' magnitude using a 0.5s windows. Error bars show the standard error. The higher value for the SD shows that the device is being moved more.

	Session Length	
App	**Mean (min)**	**SD**
YouTube	5.23	17.13
Android Video Player	6.70	15.94
Facebook	1.61	4.97
Twitter	1.52	2.57
GMail	0.77	4.92
Android Email Client	0.78	2.03
Android Browser	1.91	20.91
Chrome	1.77	6.20
SMS	0.76	2.80
WhatsApp	0.93	2.23
Google Maps	2.41	7.30
Waze	7.90	14.38

Table 3. The average session length of the 12 apps selected for the analysis. While the apps from the Media category have the longest sessions, the Messaging and Mail categories have the shortest ones.

use sessions of the apps. A use session of an app is from the time the app comes to the foreground until it goes to the background. We first determined the orientation mode when the apps were started and closed. In addition, we determined how long the phone's UI was in portrait and landscape modes as well as how often the orientation was changed in one session of use.

The average session length varies between the categories (Table 3). While the apps from the Media category have the longest sessions (*YouTube* M=5.23 minutes, SD=17.13, *Video Player* M=6.7 minutes, SD=15.94), the Messaging and Mail categories have the shortest sessions (*SMS* M=0.76 minutes, SD=2.80, *WhatsApp* M=0.93 minutes, SD=2.23, *Gmail* M=0.77 minutes, SD=4.92, *Email* M=0.78 minutes, SD=2.03). Figure 4 depicts the fraction the devices are in landscape and portrait mode. Interestingly, for the two apps in the Media category the device is on average only 28% of the time in portrait mode. Meanwhile, the devices are in portrait mode for more than 79% of the time during the use of the apps in the Browser and Social categories. For the remaining apps the devices are in portrait mode at least 70% of the time. The analysis of the data also shows that all apps start and end a session most often in portrait mode (70% of time). A likely reason that apps often start in portrait mode is that the default orientation on Android phones is portrait.

We further examined how long mobile phones are held in one of the orientation modes before they are rotated to another

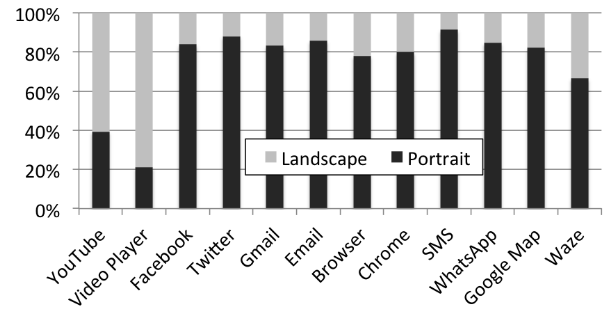

Figure 4. The use of the two orientation modes.

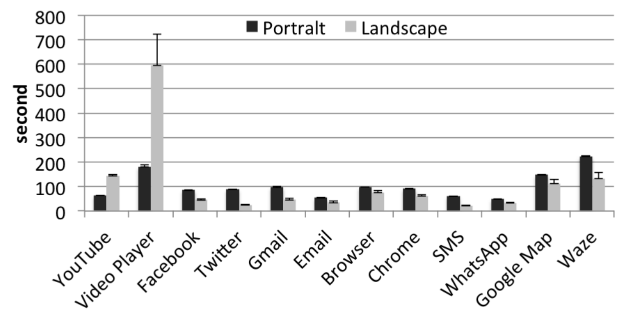

Figure 5. The average duration of an orientation mode (error bars show the 95% confidence interval).

mode as well as the frequency of orientation transitions in one session of use. Figure 5 depicts how long a phone is held in each orientation mode before the orientation is changed. The results convey that users mainly hold their phone sideways (landscape) when they use *YouTube* and *Video Player* before they rotate the phone. The phone is mainly held upright during the use of the other apps. Figure 6 shows the average number of orientation changes per minute. The analysis of the orientation transition frequency shows that the maximum and minimum number of orientation transitions occurs while using the apps in the Media category (*YouTube*: M=0.37, SD=0.83,*Video Player*: M=0.10, SD=0.20). Both apps in the Messaging category have a high number of orientation transitions (*SMS*: M=0.33, SD=1.04, *WhatsApp*: M=0.28, SD=0.82). The results suggest that users search and watch (fairly short) videos back and forth during the use of *YouTube*. While in the *Video Player* app the users seem to start (longer) videos and watch them till the end. The results for the messaging apps suggest that the users rotate the phone frequently while writing and reading messages.

Discussion

The results reveal that devices are often being moved while using navigation and messaging apps. Further, users interact with the considered apps mainly in portrait mode, except for apps from the Media category. The time distribution between landscape and portrait shows that the landscape mode is typically used for a short time except for the Media apps. A potential explanation is that the landscape mode is often triggered accidentally or used for text entry. The Media apps are mainly used in landscape mode. Hence, developers can mainly focus on portrait mode except for Media apps.

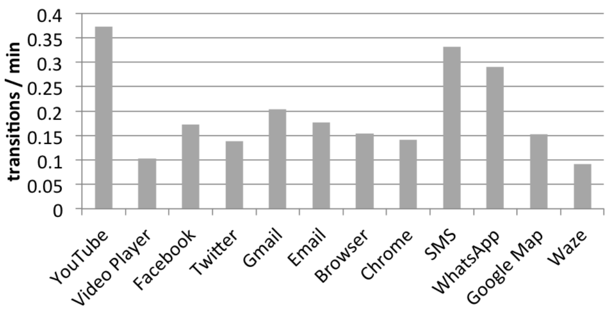

Figure 6. The average number of orientation transitions per minute.

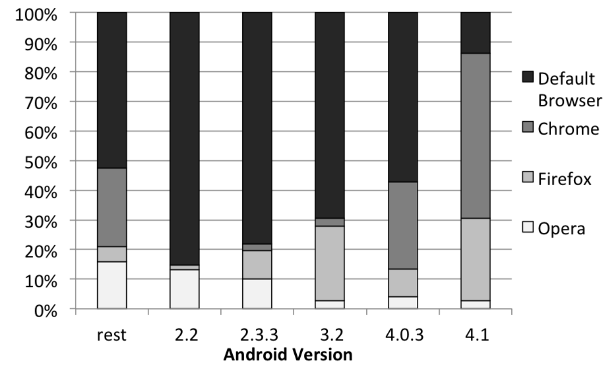

Figure 7. The use of 4 browsers on different versions of the Android OS.

Previous work states that apps are used less than a minute on average[2]. We show that the duration depends on the app (e.g., >5min. for videos, <1min. for mail & messaging) and how orientation switches fragment interaction. Looking specifically at mail and messaging apps we observe that the device is being moved more, usage sessions are shorter, and the user switches more often between landscape and portrait mode. It has been shown that movement and fragmented attention can dramatically affect the user [23, 24]. Thus, messaging apps must be specifically optimized for usage on the go. Developers need to consider ways to compensate for moving devices and fragmented attention. For example, the UI of these apps should highlight the user's last actions and offer larger controls than apps that are less in motion, i.e., video player, social, or web browsers apps. Similar to the work by Goel et al. [9] mobile keyboards should take the app's category into account.

Web Browsers	Devices	Duration
Android Default Browser	1084	54.9 days
Chrome	223	10.0 days
FireFox	124	2.7 days
Opera Mini	106	1.6 days

Table 4. The four common web browsers selected for the analysis. The table shows the number of devices on which these browsers were used and the amount of sensor data.

DEVICE ORIENTATION WHILE SURFING THE WEB

Due to the ubiquity of Internet connectivity on mobile phones today, we were particularly interested in the usage of web browsers. We observed the use of nine different web browsers in addition to the default web browser for Android phones. Since the number of users varied between apps and also between different browsers, we deliberately focused on the four most common browsers in our data set (see Table 4). Each browser has been used by at least a hundred users. At least one of the browsers has been used on 1,202 out of the 1,330 devices in the data set. Interestingly, 31% of the users used at least one additional web browser and 5% used two other web browsers in addition to the Android default web browser. In addition to the default browser, a significant number of users use other browsers. We also analyzed the use of four browsers on different Android OS versions (Figure 7). Chrome is used more on the newer Android versions, while Opera Mini is more used on older versions. The most frequent locales for the browsers are very similar to the top frequent locales for the dataset (see Table 1).

We followed the same procedure as for the other apps and first analyzed the devices' posture. We measured the duration the device was held with a particular roll and pitch. We identically binned the data as described before. The results depict that all the four web browsers also show a peak around 0/0 meaning that the device is held parallel to the ground with the screen facing upwards. The high values are mainly concentrated along the pitch axis. Using all browsers the device is almost exclusively oriented upright and the top of the screen is slightly tilted away from the user. In comparison with Figure 2 we observe a similar posture as for the *Facebook* app. For the *Opera Mini* app, similar to the *Google Maps* app, the values are also concentrated along the roll axis indicating that the device is also oriented sideways.

Orientation Spectrum in a Web Surfing Session

We also analyzed the user interface (UI) orientation of the web browsers while surfing the web following the same approach. While the Firefox web browser has the longest sessions (M=2.45 minutes, SD=5.93,), the Opera Mini app has the shortest (M=1.24 minutes, SD=1.75). Table 5 depicts the session length of the four browsers. The ANOVA test does not reveal any significant difference between the browsers ($F(3,1532)=.20$ $p=.99$). The comparison of the fraction the device is used in landscape and portrait mode, interestingly, revealed no differences between the browsers. All four browsers have a similar distribution and are used in portrait mode approximately 80% of the time across a user session (similar to the Twitter and Facebook apps).

	Session Length	
App	**Mean**	**SD**
Android Browser	1.91 min	20.91
Chrome	1.77 min	6.20
Firefox	2.45 min	5.93
Opera Mini	1.24 min	1.75

Table 5. The average session length of the four browsers selected for the analysis.

We also examined how long the mobile phone is held in one of the orientation modes before it is rotated to another mode within one user session. Figure 8 depicts how long

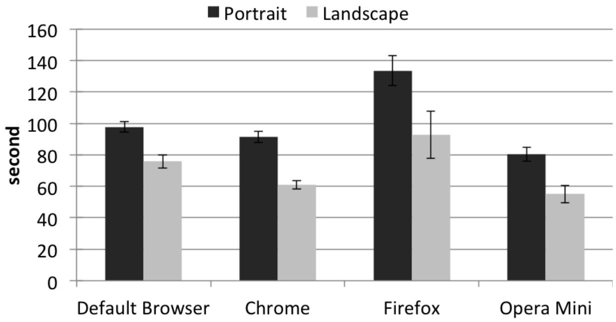

Figure 8. The average duration of one orientation mode before changing to the other. Error bars show the standard error.

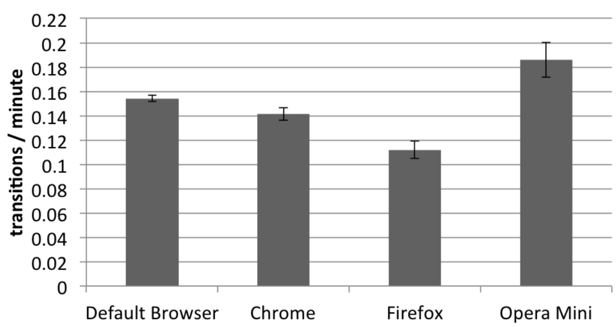

Figure 9. The average number of orientation transitions per minute. Error bars show the standard error.

the phone is held in each orientation mode before the orientation is changed. The results reveal that when users use the browsers they mainly hold the phone in portrait mode before rotating the device. We also assessed the orientation transition frequency in a session of use. Levene's test indicates that the assumption of homogeneity of variance is violated ($F(3,1532)=9.80$ $p<.001$). A one-way ANOVA shows a significant difference between the apps ($F(3,1532)=4.11$ $p<.006$). Post-hoc tests reveal a significant difference ($p<.004$) between Chrome (M=.21 transitions/session SD=.28) and Opera Mini (M=.39 transitions/session SD=.61). The difference between the two other web browsers is not significant (Android Browser: M=.29, SD=.44, Firefox: M=.28, SD=.44). Figure 9 shows the average number of orientation changes per minute. The results suggest that users might rotate the phone back and forth during surfing the web in a brief manner to read or enter text or watch a video.

Duration of Web Surfing on Mobile Phones

As we collect information about the app used we also know which app was used before a web browser is launched. Thus, we assessed whether the duration of web browsing use sessions varied based on previous apps. In general, a web browser app on the Android phone can be launched in two ways: first, the browser can be directly started by tapping the app's icon (called via *launcher* from now on in this article). Second, the app can be launched by another app. In the second case, a web browser is launched when users click on a URL address. In our dataset we have 3,937 different apps that ran right before one of the web browsers was launched.

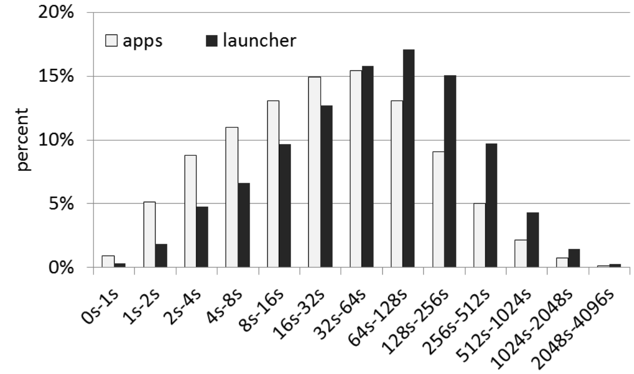

Figure 10. The histogram of the browsers' session durations when started through the launcher and through another app. The durations are binned using a logarithmic scale. It is shown that if a browser is started through apps the duration tends to be shorter than if the browser is started through a launcher.

Category	App	Devices	μ(web browsing) minutes
Mail	Android Email Client	44	1.780, SD=1.55
	Gmail	139	1.766 , SD=1.46
Social	Facebook	152	1.524, SD=1.17
	Twitter	39	1.155, SD=.54
News	Flipboard	22	1.522, SD=.71
	Google Reader	18	1.521, SD=.84
Messaging	SMS	40	1.537, SD=1.28
	WhatsApp	44	1.148, SD=.80

Table 6. The eight apps (from four categories) used right before launching the web browsers considered for the analysis. Fourth column shows the average browsing session duration based on the app previously used.

In the first step, we compared the session duration when users directly started the web browsers through the launcher with the session length when the web browsers were launched through another app. We considered data from users who started the web browsers either way, resulting in 666 users. A paired samples t-test reveals a significant difference between the average session length of the web browsers when started through the launcher (M=2.36 minutes, SD=1.57) and when started from another app (M=1.52 minutes, SD=1.14), $t(665)=15.03$, $p<.0001$ $r=.50$. The effect size indicates the difference is large, and therefore substantive. The logarithmic histogram of the session durations when started through the launcher and through another app is shown in Figure 10. If a browser is started through apps the duration tends to be shorter than if the browser is started through a launcher.

Further, we assessed the session length when the web browsers are started from within different apps. Many apps observed were used very few times or only by few users. Hence, we deliberately considered apps that had at least 15 unique users and whose users launched the browsers from within these apps at least five times. This resulted in 22 unique apps. We selected four common and popular categories (Mail, Social, News, and Messaging) and chose two most popular apps in each category for our analysis. The categories and apps selected are depicted in Table 6. We considered two apps per category to prevent results from being solely based on one specific app. A one-way ANOVA revealed that the previously used app has a significant effect on the usage duration ($F(7,497)=2.10, p<.05$). However, post-hoc tests did not reveal significant difference (all $p>.05$). The average duration of the browsing sessions when the browser is started from different apps in Table 6. The results reveal that switching back and forth between apps and the browsers and using the browsers vary.

Implications

The analysis of the data collected reveals several implications that developers should take into account.

Using another web browser in addition to the Android default web browser is common. As 31% of the users use at least two web browsers on their phones, this shows that it is common to use another web browser in addition to the default web browsers provided by the Android platform. This can be due to the extra features other web browsers provide. With the Chrome web browser on the desktop, for example, it is possible to send web pages to the Chrome web browser on Android phones. Further, various add-ons can be installed and added to the Firefox web browser app. This suggests that developers should not only focus on default browser but should also support other common mobile browsers.

Users hold the phone upright when surfing the Web. The analysis of the device's orientation for the browsers showed that users typically hold the phone parallel to the ground with the screen facing upwards or upright and the top of the screen being tilted away while surfing the Web. Looking at the time distribution between landscape and portrait mode, browsers are often used in portrait mode. Thus, developers can optimize their websites for this orientation.

Web browsers are rarely used on the go. The analysis of the standard deviation of the acceleration vector's magnitude shows that when the web browsers are used, the phone is being similarly moved as, for example, when the Facebook app is used. The comparison with other apps suggests that the device is less in motion when mobile browsers are used. This suggests that mobile browsers are less often used on the go.

Users switch back and forth between apps and web browsers. We show that explicitly starting web browsers through the launcher results in 1.5 times longer sessions compared to starting browsers from other apps. This can be due to the user's personal context such as user's goals [16, 18]. The shorter browsing sessions when a web browser is launched from an app, depicts that users switch back and forth between apps and the web browsers. This can delay task completion, create interruptions, and generate overload for users [19]. This suggests that a tight and smooth integration of web browsers with native apps can improve the overall usability. To ease the switch, developers can either include in-situ web views in their apps or provide means that allow users to easily recover after switching back to their app. Further, it is necessary to consider means for users to quickly accomplish their goals by easily moving content back and forth between apps and browsers.

LIMITATIONS AND ETHICAL CONSIDERATIONS

We conducted the study in the wild without direct contact to the users of the devices. While this approach has obvious advantages it also results in a number of limitations and ethical challenges that we discuss in the following.

Limitations

This study was conducted in-the-large and the participants are self-selected. We can provide no insights into what the users did inside the apps we analyzed. Work by Sanchez and Branaghan [29] in fact suggests that the orientation of the device and the according presentation of content can have an effect on users' ability for reasoning. Users might therefore select an orientation not only based on the type of content but also based on a particular task. However, hundreds of participants and weeks of usage are required for the conducted analysis. Our fairly large sample spans continents and different languages. In particular, collecting hundreds of participants and weeks of data is hardly possible using other methods.

Further, we only analyzed a fraction of the applications available in the Google Play marketplace and only a fraction of the applications in our data set. There are other web browsers available in Google Play. All applications we investigated, however, are rather popular, widely used, and either belong to the most downloaded Android applications or are pre-installed. The web browsers selected for the analysis, for example, were the top four common browsers in the data set collected. Based on the information from the marketplace all have been downloaded more than 10 million times and rated at least four stars.

While accelerometer sensors vary across Android devices, the characteristics of the sensor are standardized and specified in the Android Compatibility Definition Document [10]. The data provided by the sensor is similar in such a way that neither Android's higher level functions nor Android apps need to explicitly distinguish different models. We rely on much more basic characteristics of acceleration (the standard deviation of the magnitude and acceleration due to gravity). We hence assume that the accelerometers' precision and frequency are more than enough for the analysis conducted.

The orientation of the user interface results from the physical orientation of the device and does not necessarily reflect the user's intention. Cheng et al. reported based on an online survey that incorrect rotation happens frequently [3]. They report that 91% of the participants experienced auto-rotation that lead to incorrect viewing orientation. Based on our data, we cannot be sure why the orientation of the user interface changes. Unintended orientation changes, however, should only have a small effect on relative differences. In addition, unintended orientation changes only have a minimal effect on the total time a particular orientation is used.

Ethical considerations

We informed potential participants that they would contribute data to our research through the widget's description on Google Play. The description explains that the widget is part of our work as researchers. In addition, we described that the widget measures how long the apps are used and how the phone moves. Besides, the Android system informs the user about the permissions an app requires and the user needs to explicitly confirm it. However, obtaining *informed* consent is still challenging. Pielot et al. [25] showed, for example, that the way potential participants are informed has a dramatic effect on their reaction. Similarly, Morrison et al. [22] showed that telling users what is recorded, such as their position, leads to very different effects compared to showing them its meaning – in this case just showing their position on a map. Users might be aware that something is recorded but the researchers cannot ensure that they truly understand the implication.

As we could not ensure that all users fully understand the potential implications we tried to minimize potential negative effects on the user. To provide the main functionality of the widget, it was necessary to have a background service. The same service was also used to record the device's acceleration and was only active if the device's display was switched on. Thus, we minimized potential harm for the user caused through excessive consumption power or other resources. Indeed, we did not record any data that would allow us to identify the user of the device.

CONCLUSION

In this paper we present an approach to collect a large data set that combines app usage and sensor data to learn about mobile in-situ usage. Using the collected data we show that devices are being moved more while using navigation and messaging apps. In addition, we determined that all apps we investigated, except for Media apps, are mainly used in portrait mode. The time distribution between landscape and portrait reveals that most of landscape mode time is for burst interaction (e.g., text entry). Hence, app developers should mainly focus on providing usable portrait UIs.

Further, we deliberately opted for the analysis of the four most common web browsers, i.e., the default web browser on Android phones, Chrome, Firefox, and Opera Mini. We showed that devices are less in motion while users are surfing the web in comparison to using the SMS app and Google Maps. We determined that the web browsers are mainly used in portrait mode. We assume that most of landscape mode time is spent for reading and typing texts as well as for watching videos. Looking specifically at the selection of web browsers, we observed that devices are less in motion, usage sessions depend on how the web browsers are launched, and the user switches between landscape and portrait mode. It has been shown that movement and fragmented attention can dramatically affect the user [23, 24]. Therefore, developers need to be especially concerned. Developers need to provide means to enable users to compensate device movements and fragmented attention.

We collected a data set that contains more than 100GB compressed sensor data from a large number of users. This corpus of data set could enable a number of further analyzes. It might be possible to determine which apps are used while walking, distinguishing between different transportation modes, and detecting when users enter text. However, a reliable ground truth is essential for such a goal. Learning about users' activities while using different applications could be combined with a static analysis of mobile interfaces [27] and executing applications in an emulator would enable to also observe the applications' behavior. We believe that these analyses could ultimately lead to a holistic picture of mobile human-computer interaction.

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