Modeling Perceived Screen Resolution Based on Position and Orientation of Wrist-Worn Devices

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ABSTRACT
This paper presents a model allowing inferences of perceivable screen content in relation to position and orientation of mobile or wearable devices with respect to their user. The model is based on findings from vision science and allows prediction of a value of effective resolution that can be perceived by a user. It considers distance and angle between the device and the eyes of the observer as well as the resulting retinal eccentricity when the device is not directly focused but observed in the periphery. To validate our model, we conducted a study with 12 participants. Based on our results, we outline implications for the design of mobile applications that are able to adapt themselves to facilitate information throughput and usability.

ACM Classification Keywords
H.5.2. Information Interfaces and Presentation (e.g. HCI): User Interfaces

Author Keywords
Perception; modeling; wrist-worn devices.

INTRODUCTION
Smartphones are available with display sizes varying from 2.2 to 7 inches with screen resolutions up to 800 pixels per inch (PPI), while wrist-worn devices have even smaller screens, typically below 2 inches with resolutions of up to 400 PPI. With current developments such as the Apple Watch 3[1] or the Samsung Gear S3[2], sophisticated devices are available. Based on recent forecasts, the market size is expected to grow to over 80 million sold wrist-worn units per year by 2021 [5]. Eye-worn displays have, by design, a perceived screen size/resolution that is different from the hardware – similar to projected displays, e.g. of hand-held projectors where screen size and resolution depend on projection distance and angle.

[1] www.apple.com/watch/, last accessed 05/01/2018
[2] www.samsung.com/gears3, last accessed 05/01/2018

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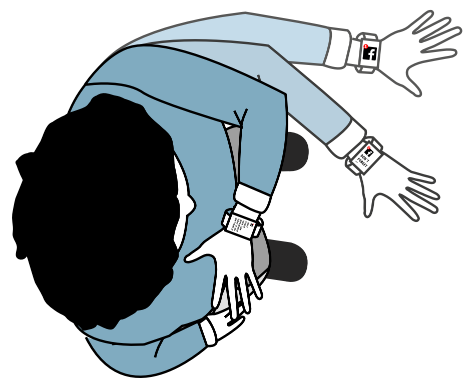

Figure 1. Example use case of the proposed model: Different levels of detail are shown depending on perceivable screen resolution based on the device's position and orientation in the field of view.

Delivering visual content in an appropriate manner to this large variety of screens is a challenging task, especially when targeting the smaller screens. It is thus not surprising that many smartwatches are currently only used as auxiliary screens of connected smartphones [31], e.g. to deliver notifications as the wrist-worn devices are able to provide them with faster accessibility compared to smartphones [1, 12]. However, screen content might not be easily perceivable for users, as the wrist-worn devices are often not in the central field of view, but only in the periphery of the user (cf. Figure 1). This leads to a reduction of the perceived resolution due to two main factors. Firstly, depending on the position of the arm and the orientation of the head, the screen will be tilted and thus only a fraction of the screen space will be visible, reducing the overall visibility of the pixels. Secondly, the acuity of human visual perception is much lower in the periphery of the field of view. Only about 2°, known as the fovea centralis, offer a very high resolution and good chromatic vision. Towards the periphery, resolution and chromatic sensitivity drop rapidly. In contrast, the ability to sense movement is increased towards the periphery. Consequently, it does not seem beneficial to display certain types of screen content, e.g. small notification icons, when the device's display is not directly observed by the user. Currently, user interface designers need to rely on their intuition and experience to tailor content for different types of screens. There are no models or guidelines available that would help them to either inform the visual design according to the perceived resolution or to simulate the visible content given a certain position of the device, the head, and eyes of the user. Several attempts have been made in the past to include the proximity of the user in the interaction with displays in the environment of the user. By adapting the concept of Proxemics by Hall [10], Ballendat et al. [2] adapted possible in- and output of environmental displays. Vogel and Balakrishnan proposed to use the distance of a user from a public display to change the possible interaction techniques from implicit to explicit [35]. Besides the change in interaction technique, the displayed content would also change from impersonal notifications to personal information such as emails.

We extend this work towards wrist-worn displays by providing a model that allows prediction of an effective resolution that can be perceived by a user depending on proximity and tilt of the device in question. We validate our model based on a laboratory study with N=12 participants and discuss meaningful use cases in which adjustments of user interfaces based on corresponding predictions could be beneficial.

RELATED WORK

There exists a broad range of related work that focus on peripheral vision on displays in the environments (e.g. [17, 18, 19]). In contrast, near-eye displays have also been investigated [6, 15]). To us, the area of interaction with wrist-worn devices is broadly of interest, especially considering output concepts. Furthermore, we will discuss related work in the area of perceptual modeling as the background for our model.

Output on wrist-worn devices

While a lot of research focuses on input on small wearable devices, the limited size makes output difficult as well. One of the earliest interactive wrist-worn devices was developed by Hansson and Ljungstrand [11]. Their Reminder Bracelet allowed a connected PDA to notify the user using integrated LEDs. With Damage, Williams et al. presented a wearable ambient display that allowed for semi-public notifications using LEDs as well [36]. Pasquero et al. investigated tactile output on a smartwatch [23]. Besides notifications, they found it to be suitable for obtaining numerical data as well.

The multiple display segments of the Facet system [16] were able to overcome the problems that arise from the small display size of current devices. On the one hand, the multiple viewing angles allowed for different relative head positions, and on the other, the ability to stretch applications over multiple display segments reduced the effect of the small display size. Nevertheless, the system not only requires a high amount of hardware, but also did not adapt automatically to the user's context, instead relying on manual adaption.

Prior research indicates that smartwatches are ideally suited for simple output functionalities (e.g. [1, 12]). However, current developments and changes in the typical use cases make it necessary that user interface designers get a better understanding of the perceptual constraints these devices impose to fully exploit their capabilities. We go one step towards understanding these constraints by providing a perceptual model that can be used for simulations, but also to automatically adapt content and interaction capabilities.

Perceptual modeling

Perceptual models are widely used in fields that are concerned with visual output, ranging from computer graphics [3] to information visualization [34]. These models help to determine how visual output has to be generated to be of maximal use to the user while at the same time minimizing computational effort. For our purpose, we need to investigate those models that are able to predict the perception of a small display located at an arbitrary position in the visual field of the user.

There are a number of systems that detect the distance and relative position of the user to the display and use this information to optimize the displayed information based on perceptual considerations. E-conic [21] is a system that uses a tracking system to adjust the rendering of information on an screen located at an arbitrary position relative to the user to appear perpendicular to the user, thus making information accessible more easily. SpiderEyes [7] is a system/framework that gathers contextual information about users interacting with a large display and predicts attention based on position and view direction of the user, allowing the system to determine which information is currently most relevant to the user.

The second group of related models comes from the efforts to build gaze-contingent (multi-resolution) displays (GCMRDs): systems that use not only coarse position information but also accurate eye-tracking to detect the gaze location of the user and eliminate information that is not visible due to limitations of human perception, e.g. low peripheral acuity. However, it is important to note that models for GCMRDs often are conservative in their predictions, i.e. they can predict a threshold for information that is guaranteed to be imperceptible, but they cannot guarantee that the displayed information is perceptible. Based on perceptual considerations, a number of different systems and approaches have been developed [8, 9, 29, 33]. The model proposed by Reddy [27, 28], for example, predicts contrast sensitivity throughout the visual field based on eccentricity, i.e., how far from the center of field of view the object is, and movement of an object. The model itself is grounded in perceptual research about the make-up of the retina [30] and incorporates another model for the decline of visual acuity for moving objects [22].

By extending related work, we will provide a model that allows the right presentation based on display properties (e.g. size, orientation) with respect to the user. We first present the underlying adaption model and outline possible use cases for this adaption process afterwards.

MODEL OF PERIPHERAL DISPLAY PERCEPTION

In order to predict what information is visible to the user, we model some aspects of the human visual system (HVS). The model we are using is based on the work by Reddy [27, 28], who built his model to predict the perception of virtual stimuli based on their location in the field of view. Reddy bases his model especially on the the notion of the cortical magnification factor from [30] to approximate the contrast sensitivity function (CSF) across the visual field. We will use the model to compute the highest spatial frequency that is visible on a display, extending it to take into account the relative location and rotation of the display.

We specify the display D with the vertices P_1, P_2, P_3, P_4 as well as its resolution res_x and res_y along its x and y axis. We assume that the observer is located at the center of the coordinate system, facing in the direction of the positive y axis and with a maximal visual acuity of $res_{fovea} = 60$ cycles per degree [37] in the center of the fovea. We talk about the display dimensions in units of visual angle (°), the size of an object projected on the retina, and the resolution in cycles per degree.

As a first step, we calculate the observed size of the display; that is, how large the display appears in the field of view. This means that two objects of the same size can have a different apparent size, if they are located at different distances from the observer. We determine the observed size by calculating the angle between the vectors from the observer to the centers of the edges of the display that are furthest apart:

$$v_x = \measuredangle P_{top} P_{bottom} \quad (1)$$

$$v_y = \measuredangle P_{left} P_{right} \quad (2)$$

This discounts slight differences that occur at the edges due to perspective; however, we expect those effects to be rather small. The sensitivity of the HVS can be predicted using a scaling factor M that depends on the eccentricity of the observed point. We use a formula created by Reddy [27, 28] to calculate M. They synthesized the formula from vision literature and experimental data:

$$M = \begin{cases} 1, & \text{if } E < 5.790. \\ 7.49/(0.3E+1)^2, & \text{otherwise.} \end{cases} \quad (3)$$

M is then used to scale the maximal available resolution of the fovea to predict the highest visible spatial frequency:

$$res_{eye} = M res_{fovea} \quad (4)$$

Based on these values, we can calculate the observed resolution of the display. We know the spatial frequency of the display based on its resolution and observed size and use the highest visible spatial frequency as a cut-off for what can be observed. From this, we get the resolution in cycles per display axis by multiplying with the size of the display.

$$vres_x = min(\frac{res_x}{2v_x}, res_{eye}) v_x \quad (5)$$

$$vres_y = min(\frac{res_y}{2v_y}, res_{eye}) v_y \quad (6)$$

To visualize the predictions of the model, we provide a tool that – given a display position and orientation in relation to the user's eyes – renders a picture representing the effective display resolution, e.g. to assess text readability for different sizes or fonts. We distinguish whether a person is (a) directly looking at the display or (b) looking straight ahead and observing the display in the periphery. The tool takes a picture, e.g. a screenshot of a smartwatch application, converts it to the CIE L*a*b* space [20], and only the luminance information is further considered. A second-order Butterworth filter [4] is used to remove frequencies that would not be visible according to our model. Figure 2 shows an example for a display with an edge length of 20 mm and a resolution of 200 × 200 pixels. The tool is available on GitHub[3].

[3] https://github.com/fkerber/perception-model-tool

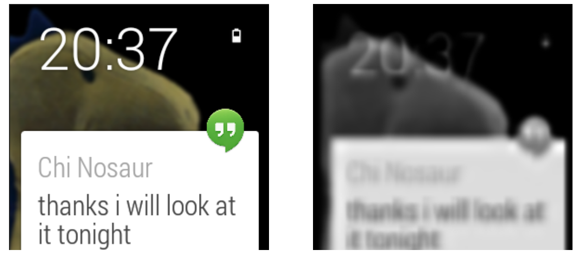

Figure 2. Input image and prediction for a square display with an edge length of 20 mm and a resolution of 200 × 200 pixels of a distance of 40 cm from the observer and an angle (horizontal, vertical) of (10°, 20°).

USER STUDY

To validate our perceptual model, i.e. to assess the accuracy of our predictions for the effective display resolution dependent on position and orientation relative to the observer, we conducted an empirical user study with the goal to measure a user's ability to perceive certain types of content on the device's display and to compare these findings to our predictions.

We recruited 12 participants (5 female) aged 22-33 (M=26.1 years) that stated they did not need glasses for near vision. We first conducted a near-vision test at a distance of 16 inches (around 40 cm) to determine visual acuity in the range 20/200 to 20/20 in Snellen notation [32] in which all participants reached comparable values in the range 20/32 to 20/25.

Apparatus and Experimental Design

We conducted our evaluation using Landolt rings, a standard stimulus used in vision tests. The symbol used – the Landolt C – is a ring with a gap at one of eight positions (top, right, bottom, left and the 45° positions in between). The subject's task is to decide at which position the gap is. In contrast to using a Snellen chart, cognitive recognition and similarity only play a subordinate role [26]. To cover the typical interaction space of a wrist-worn device, we sampled positions in the typical comfort zone for the left arm. Considering the participants' eye position (defined as the central point between both eyes) as the point of origin, the target positions are placed at a distance of 40 cm, as it is the canonical distance for near-vision tests [13]. However, the results are not tied to the distance, as the measurements give information about the angular resolution, which can be generalized to other distances. Four horizontal directions (0°, 22.5°, 45° and 67.5°) and three vertical ones (-30°, 0° and 30°) were combined to generate a set of twelve sample points that cover a large area of the typical field of view (requiring only the left half due to symmetry).

To be able to reliably test the perception at the sample points under realistic conditions, we constructed an apparatus that enabled us to place a smartwatch (Simvalley AW-414.Go) at the target positions (see Figure 3). The device provides a display with a screen diagonal of 1.54" and a screen resolution of 240 pixels × 240 pixels that is oriented orthogonally to the viewer. Based on the given screen resolution, Landolt rings with a gap size up to 48 pixels could be displayed.

To ensure that the distance and orientation between device and participant remained stable, a chin rest was used. As we primarily focused on peripheral vision, we instructed our

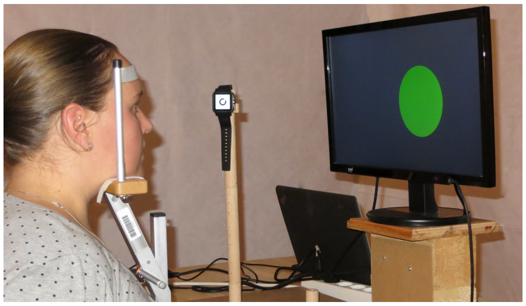

Figure 3. Study setup in the laboratory environment.

participants to always look straight ahead and not to focus on the device in the periphery. To ensure this, we used a secondary display in the direct line of sight to display a green marker the participants should focus on. We checked the line of gaze by utilizing a stationary eye tracker (Tobii Eye Tracker 4C[4]) mounted on the display. Whenever we detected a deviation from the marker (indicated by coloring it red), we cleared the smartwatch display and displayed another stimulus of the same size as soon as the user again focused on the marker.

At each position we conducted a staircasing procedure to assess the user's ability to perceive the position of the gap. We always started with a medium-sized stimulus (gap size of the Landolt-C 25 pixels) and adjusted the gap size for subsequent trials based on the *Best PEST* approach [14, 24] taking prior answers into account. The participants indicated the location of the gap verbally so the experimenter could record the response and trigger the next stimulus.

Before each stimulus presentation, we displayed a sequence of three random noise patterns for 200 ms each as distractor. The procedure was terminated after 50 recorded answers and then repeated for the remaining sample positions (in balanced order to rule out sequence or fatigue effects).

Hypothesis and Measures

We formulate the following hypothesis: For all examined positions and orientations of the smartwatch, the measured visual acuity correlates to the predictions from our perception model. As a measure for visual acuity in our setup, we consider the smallest gap size that could be reliably detected (as provided by the Best PEST procedure after 50 trials).

Results

The results in terms of smallest reliably detectable gap size for our twelve sample points are shown in Table 1 (Mean values for N=12 participants) along with the predictions of our model. As the predictions of our model are issued in *cycles per axis* (CPA), we transfer the observable gap sizes (in pixels) accordingly. For the second sample point (that maps to direct observation in the fovea), the computed values are cut off by the actual display resolution (i.e. the values would not increase further just because the display gets closer). For the sample points at the outermost horizontal position (67.5°), as well as those in the 45° horizontal direction and $\pm 30°$ vertical direction, the display resolution of 240×240 pixels was potentially not sufficient to display a Landolt ring in a reliably recognizable size for many participants. In this sense, a reported value of 48 pixels is to be interpreted as a lower bound here; the actual value might be larger. Hence, we excluded corresponding values from further analysis.

Hor. angle (°)	Vert. angle (°)	Min. obs. gap size (Pixels)		(CPA)		Prediction (CPA)
		Mean	SD	Mean	SD	
0	-30	26	7.9	18.5	6.0	17.8
0	0	1	0.0	120*	0.0	120*
0	30	31.7	9.5	15.2	5.0	17.8
22.5	-30	31.7	4.6	15.4	1.4	12.3
22.5	0	13.9	6.9	34.5	3.4	29.7
22.5	30	40.8	3.0	11.8	0.8	12.3
45	-30	*(46.5)*	*(7.8)*	*(10.3)*	*(4.1)*	6.4
45	0	31.6	3.0	15.2	6.7	8.5
45	30	*(46.4)*	*(7.5)*	*(10.3)*	*(2.7)*	6.4
67.5	-30	*(47.75)*	*(0.9)*	*(10)*	*(0.2)*	3.6
67.5	0	*(47.1)*	*(2.2)*	*(10.2)*	*(0.5)*	3.9
67.5	30	*(48)*	*(0.0)*	*(10)*	*(0.0)*	3.6

Table 1. Results of our validation study in terms of smallest reliably detectable gap size (Mean for N=12 participants) along with the predictions from our model. Values indicated with a * are capped due to the display resolution of 240 pixels per axis. *(Values)* are subject to limitations by the maximum displayable Landolt ring size with a gap size of 48 pixels.

We calculated a linear regression with the remaining 87 samples to fit the model to our own data and provide a more accurate formula representing our experimental results. We found a statistically significant regression equation ($F(1,85) = 4223.632, p < .001$), with an R^2 of .98. The adjustement to the initial model is $4.278 + 0.964 * (InitialPrediction)$. A visual presentation of the observed results in comparison to the predictions of our model is depicted in Figure 4. Again, the values for the blue line at the leftmost positions are expected to be lower, i.e. the model fit could be even better if we were able to test with a higher maximal apparent resolution.

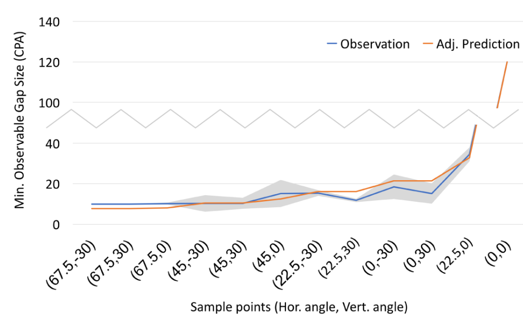

Figure 4. Comparison of our predicted values (adjusted by the outcome of the linear regression analysis) along with the observed ones. Shaded area presents the standard deviation for the observed values. The sample positions are shown in ascending order based on predicted values.

Discussion

Following our results, we can confirm our hypothesis and validate the model based on 87 sample points from 12 participants. The remaining sample points we tested follow the same direction as predicted by the model, but due to the display resolution, an exact determination of the threshold value could not be achieved. While we only tested the left hemisphere

[4] https://tobiigaming.com/eye-tracker-4c/, last accessed 05/01/2018

(considering the device being worn on the left wrist), the results can easily be transferred to the right hemisphere as the geometrical properties are analogous. The results show that for a typical smartwatch–user distance of 40 cm, meaningful predictions for the perceived screen resolution can be made.

USE CASES

A model that allows prediction of perceivable screen contents provides the possibility to define areas with similar properties. As perception directly influences how people can interact with a device, we name these areas *interaction zones*. Consequently, the question arises how a user in general, or more specifically which applications, can benefit from such zones. We outline meaningful use cases and show how applications can adapt their interaction concepts according to our interaction zones.

Level of detail adjustment Mapping the device's distance to the user provides the possibility to represent different levels of detail. Considering, for example, message notifications (email, Facebook, WhatsApp, etc.), in a coarse overview large application icons can be shown (referred to as "abstraction" in [19]). If the device's position allows for more information to be perceived by the user, details such as the message's issuer could be added. When the device is directly focused, the complete message text could be displayed (see Figure 1 for a visualization of the described use case). In this sense, the adaptation can also be interpreted as mapping of interest or engagement (cf. [25]). Transferring the level-of-detail concept to a map navigation application, coarse information could be large symbols for turn-by-turn instructions, whereas a more fine-grained view could show details about crossings or a detailed map view with street names. The presented model can be used to decide which level of detail should be displayed based on the device's distance and orientation to the user.

Adaptive touch targets A distance mapping can also be used to adapt the design of user interface elements. As the user cannot see and act precisely if the device is further away, fewer but larger displayed options should be shown, whereas small distances permit more options. A use case is a music player that shows a single, large play/pause button in the periphery for gaze-free interaction and more detailed options, e.g. to perform playlist selections, if the device is in a position that allows better perception.

Proximity-based input selection The device's distance to the user may be used to trigger input modes. If for example the device approaches very close to the user's mouth (so that the display cannot be observed anymore), speech recognition could be activated. If the device is easily reachable with the user's (dominant) hand and clearly observable, a keyboard could be displayed, as the user should then be able to interact with the typically small buttons on it.

Energy-saving The predictions can also be used to save energy by adjusting the display state (on/off) and brightness/contrast based on how visible the content of the devices is within the field of view. This could improve existing adjustments that use other sensors like surround brightness or in-pocket detection of phones.

CONCLUSION AND FUTURE WORK

We presented and validated a model that allows inference of perceivable screen content on wrist-worn devices given their position in relation to an observer's eyes. The model is built on insights from vision science and considers properties of the human visual system to predict what information is visible to an observer. As a first step to provide useful tools for user interface designers, we implemented a tool to visualize how a given type of screen content is perceived depending on the distance and orientation of the smartwatch display w.r.t. to the observer. We thereby distinguish whether the device is actively observed, i.e. the user is directly looking at the display, or whether it is located in the peripheral field of view. Given the output of our model, user interface designers can adapt the visual appearance of their applications in a way that assures that users are able to perceive the desired screen content.

Limitations

The laboratory setup in which we validated our model gave us the advantage of restricting the position and orientation of both, user and smartwatch to known values. Furthermore, due to ideal lighting conditions, effects such as contrast decreases due to sunlight could not be taken into account. Due to the ongoing miniaturization of hardware and constant increase in computing power, a wrist-worn device with an integrated (depth) camera could be used instead to track the distance to a user's head. Given such a device, an in-the-wild study would be beneficial to test our hypothesis in a more realistic usage scenario. The conducted investigation based on 12 participants with normal eyesight does not guarantee that the model is transferable to a wider audience, e.g. with corrected-to-normal eyesight, as for example glasses might influence the perception in the periphery. The limited screen resolution does not provide the possibility for a detailed investigation towards the outer areas of the observable field in the periphery.

Future Work

As a next step, we will derive specific guidelines based on the proposed interaction zone concept and evaluate them based on prototypic device implementations. Although we already outlined zones with meaningful distinction on the output as well as the input side, it is still an open question where exactly the borders of these zones can be found. Furthermore, it is worthwhile to investigate whether we have to consider user-dependent preferences (apart from vision-related aspects which should be integrated in the prediction, or physical properties such as arm length) or whether the same zones are suitable for a general audience. Consequently, adaptive applications have to be developed to evaluate these aspects in a user study focusing on user experience and preference. In addition, a wider audience, e.g. wearers of glasses or contact lenses, could be investigated with our apparatus. Also, other aspects such as the influences of color contrast could be taken into account.

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