# Exploring Eye Adaptation in Head-Mounted Display for Energy Efficient Smartphone Virtual Reality

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## ABSTRACT

Smartphone virtual reality (VR) can offer immersive experience while being affordable and easy to use. To enhance the VR experience under limited smartphone computation and battery resources, solutions have been proposed for efficient rendering and content delivery. However, efforts towards optimizing the distinct head-mounted display (HMD) are unfortunately limited. This paper unveils the opportunity of optimizing smartphone VR by leveraging human vision in HMD. In particular, we shift the default fixed full brightness in VR video/game Apps to a dark adaptation based dynamically scaled brightness. By exploiting the time-varying sensitivity of human eyes in dark HMD, we can reduce VR display energy while maintaining brightness perception. The proposed system, Strix, is empowered by a dark adaptation model trained from classic experimental data, a varying trend of perceptual full brightness derived from the dark adaptation model, and a smooth brightness transition scheme balancing energy and experience. Experimental results show that Strix can achieve 25% system energy reduction without negatively impacting brightness perception.

## CCS CONCEPTS

• **Information systems → Mobile information processing systems**;

## KEYWORDS

Energy; head-mounted display; smartphone; virtual reality

## 1 INTRODUCTION

The market of Virtual Reality (VR) is boosting exponentially. The first quarter of 2017 has witnessed a 70% increase in global shipment of VR units over the same period in 2016 [8]. Among different types of VR, smartphone VR has accounted for an impressive 67% of the global shipment [8]. Unlike a tethered VR headset wired to a desktop (e.g., Oculus Rift), in smartphone VR (e.g., Google Cardboard), a smartphone is inserted into a head-mounted display (HMD) in order to render and display the VR content. Although smartphone VR enjoys the mobility since no extra wire is needed, such systems have limited battery and processing resources.

Despite the efforts on improving graphic rendering [3, 15] and content delivery [16, 21] in VR, studies on optimizing smartphone VR display is still limited. Unfortunately, HMD happens to be the most distinct component within VR systems. It has shown unique effects on human vision that one would never experience on regular mobile displays, such as binocular vision rivalry [25], misjudgment of distance [18], and vergence-accommodation conflict [14]. How can we harness the unique visual effects in HMD and design efficient smartphone VR systems remains unclear. In this paper, we take an exploratory step and unveil the opportunity of leveraging HMD vision for smartphone VR optimization. We focus on *eye adaptation* within HMD and utilize this special effect to optimize the display energy in smartphone VR.

In particular, modern smartphones apply a fixed full brightness by default to guarantee a satisfactory viewing experience in video or game Apps. According to our measurement, the display under such a setting can consume a significant percentage (47%~51%) of system power in smartphone VR (Section 2). On the other hand, users wearing HMDs watch the VR content in a dark environment without seeing any ambient light. Human eyes will then experience a physiological effect, called *dark adaptation*, where the sensitivity of eyes is gradually increasing as one spends more time in the dark. Consequently, a lowered screen brightness in HMD could produce the same brightness perception that one would have achieved under the full brightness in normal lighting. Hence, the objective of this paper is to replace the default fixed full brightness by a dark adaptation based dynamically scaled brightness in order to minimize smartphone VR energy. The ultimate goal is to shift the mobile displays that has entertained users for decades to a new HMD vision based display specifically designed for smartphone VR.

Achieving the objective is non-trivial and requires us to overcome two daunting challenges. First, eye adaptation was discovered by studying the luminance threshold of light source that can trigger eyes' response. How to formally model such an effect and map the luminance threshold to the brightness level in operating system (OS) that can support HMD viewing is not yet clear. Second, dynamic brightness dimming, if operated inappropriately, can easily incur the annoying flicker effect. While an extremely high scaling frequency (the number of brightness change per unit time) may result in a smooth viewing [12], it may also diminish the energy saving. This is because frequent and consecutive dimming requests may not be completed in time due to the hardware response time of each dimming [17]. These dimming requests would be postponed one by one, which slows down the brightness dimming.


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To tackle these challenges, we present *Strix*, an energy-efficient smartphone VR display system that exploits the dark adaptation to dynamically scale the screen brightness while preserving the viewing quality. Based on a classic physiological study, we train a dark adaptation model using nonlinear regression. Furthermore, by utilizing Weber's Law and a luminance measurement study, we map the adaptation trend of luminance threshold to *perceptual full brightness* in HMD, i.e., the time-varying lowered brightness that can produce a full-brightness perception in smartphone VR. Moreover, we identify the optimal scaling frequency in Strix by considering both flicker perception and display energy.

We have prototyped Strix on commercial off-the-shelf smartphone VR systems. Strix can support any legacy VR Apps and balance energy saving and viewing experience based on an adjustable user knob. We validate Strix designs under various practical settings including VR App type, display type, and VR session duration. The results show that Strix can save an average of 25% system energy with a comparable experience to conventional full-brightness VR display.

To summarize, the contributions of this paper include:

- A HMD vision driven energy-efficient smartphone VR display that exploits eye adaptation (Section 3).
- A set of designs that guide the brightness scaling, including a dark adaptation model specifically for HMD and a smooth transition scheme (Section 3).
- A practical demo of using HMD vision to save display energy while maintaining user experience (Section 4).

# 2 BACKGROUND AND MOTIVATION

## 2.1 Smartphone VR Display Power

Smartphone VR is entirely powered by mobile battery. Due to the larger content size and more intensive processing, it is expected to be even more power-hungry than regular smartphone systems. Display is usually the most energy-consuming component (up to 67%) in regular video/game Apps [5, 27]. Considering the added rendering and/or networking power for VR content, the percentage of display power may be reduced in smartphone VR. Therefore, we measure the display power in smartphone VR and confirm its persistent significance.

Figure 1 shows the system power of a 300-second session with display on and off for both VR video (remote) and VR game (local). We use LG Optimus G Pro in an office WiFi network. Details on measurement setup for VR can be found in Section 4. By differential measurement [11], we can obtain the display power of 1754 mW and 1704 mW, which are equivalent to 47% and 51% of system power, in VR video and VR gaming, respectively. This indicates that despite the slightly decreasing percentage, display power is still one of the dominant energy source in smartphone VR. Hence, it is *desirable* to minimize the HMD display power.

Despite the distinct mechanism of Liquid crystal display (LCD) and organic light-emitting diode (OLED), one common energy-saving approach for both displays is to uniformly dim the screen brightness [9, 11]. This can be achieved by decreasing the backlight level of LCD [27] or scaling the supply voltage of OLED [22]. In order not to limit our designs to LCD or OLED, we herein focus on this approach and collectively term it as *brightness scaling*.

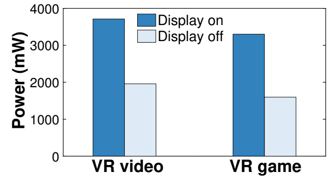



**Figure 1: VR display power is still significant.**

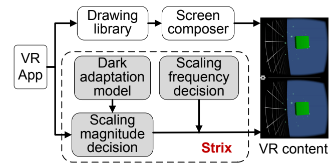



**Figure 2: Architecture of Strix.**

## 2.2 Dark Adaptation

Human eyes can sense an extremely large range of light levels with the brightest and darkest perceivable light level being a factor of $10^9$ apart [4]. However, at any given moment, one can only differentiate light sources with a contrast ratio of $10^3$ [4]. The wider perceivable range is achieved by *eye adaptation*, where human eyes dynamically adapt their definition of what is bright. In a dark environment, human eyes perform *dark adaptation*, i.e., dynamically decreasing the definition of what is bright (increasing eye sensitivity). For example, when a user using the smartphone at full brightness steps into a dark room from a normal lighted room, her eyes will usually be uncomfortable because the screen is too shining considering her increased eye sensitivity.

Dark adaptation is a classic physiological effect and there is a wealth of studies on it. The dark adaptation experiments aimed at finding the minimum luminance of a light source that triggers a visual sensation. Such a *luminance threshold*, can be found by continuously increasing the luminance of the light source until the subject reports its presence. By measuring this threshold after the subject has stayed in the dark room for different periods of time, studies have found that luminance threshold gradually decreases as the time spent in the dark increases [20]. For example, the luminance threshold can decrease three orders of magnitude in 20 minutes [20]. This provides us an opportunity to reduce the brightness in smartphone VR while preserving the brightness perception. Thereby, it is *feasible* to exploit eye adaptation to reduce HMD energy.

# 3 STRIX DESIGN

Figure 2 shows the architecture of the proposed system, Strix. Strix runs within a VR App in parallel to the regular VR rendering. When the VR content is rendered/decoded, Strix will determine whether or not the smartphone brightness should be scaled at the upcoming moment and how much it should be scaled. The final display will then generate a combined perception of the rendered frame and the scaled screen brightness. Specifically, Strix leverages a dark adaptation model that we build upon classic physiological data. Since classic dark adaptation focuses on the luminance threshold that can trigger a sensation, Strix also converts the trained model to obtain the luminance that is perceived as full brightness level and accordingly determines the scaling magnitude. Moreover, Strix applies an optimal scaling frequency to strike a tradeoff between flicker perception and energy saving. In the following, we will describe each Strix module in detail.

**Table 1: Model Parameters**

| $\theta_1$ | $\theta_2$ | $\theta_3$ | $\theta_4$ | $\theta_5$ | $\theta_6$ | $\theta_7$ |
|---|---|---|---|---|---|---|
| -1.97 | 1.39 | 1.61 | -0.23 | 8.7 | 0.18 | 19.43 |
| RMSE: 0.1296, $R^2$: 0.99, PCC: 0.9965, $rho$: 0.9982 | | | | | | |

## 3.1 Modeling Dark Adaptation

Although there is a wealth of physiological studies identifying the phenomena of dark adaptation [4, 20], no explicit model is available. We explore the data of an existing dark adaptation experiment and employ a data-driven method to obtain a mathematical model using the data. Figure 3 plots the data samples of the luminance threshold (blue dots) obtained in the dark adaptation experiment in [20] via the methodology described in Section 2.2. It can be seen that the luminance threshold decreases with time, indicating that the eye sensitivity increases.

As shown in the figure, there are three phases in the dark adaptation curve. In less than 10 minutes, the luminance threshold decreases exponentially with time. After staying in the dark for around 10 to 20 minutes or 20 to 50 minutes, the luminance threshold decreases linearly. However, the two linear functions vary with a different slope. Hence, we propose to model the dark adaptation as a piecewise function.

$$\Delta_{\min} = \theta_1 + \theta_2 e^{-t/\theta_3} + I(t,\theta_5)\theta_4(t-\theta_5) + I(t,\theta_7)\theta_6(t-\theta_7) \quad (1)$$

where $\Delta_{\min}$ is the luminance threshold that triggers a eye response, $\vec{\theta} = \{\theta_1, \theta_2, \cdots\}$ are the model parameters, $t$ is the time the user spends in the dark, and $I(t,\theta_i)$ is an indicator function that implies which phase the user is currently staying at. The indicator function can be expressed as follows.

$$I(t,\theta_i) = \begin{cases} 0 & t-\theta_i \le 0 \\ t-\theta_i & t-\theta_i > 0 \end{cases} \quad (2)$$

We use nonlinear regression with maximum likelihood estimation to determine the model parameters. Table 1 summarizes the trained parameters and the evaluation of goodness of model fit. The proposed model obtains a small root-mean-square error (RMSE) with respect to the range of luminance threshold and close-to-one values for R-squared, Pearson correlation (PCC) and Spearman rank correlation (rho). This validates that the model captures the data samples accurately, which can also be visualized by the fitted curve (red line) in Figure 3.

Note that human eyes may still be exposed to some low-intensity light source (compared to normal ambient light) during the dark adaptation, e.g., the low brightness screen in VR viewing. The impacts of such light exposure during the course of dark adaptation is not yet clear [2]. In this paper, we exclude the impacts of this content illumination. More details are discussed in Section 5.

## 3.2 Deriving Perceptual Full Brightness

As we discussed, due to the dark adaptation, the OS brightness level for HMD that can produce a sensation of full brightness as in normal lighting is decreased. We term such a brightness level as *perceptual full brightness*. Since the model in (1) only captures

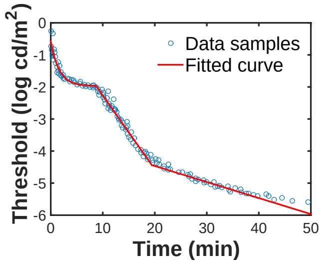



**Figure 3: Dark adaptation curve of human eyes.**

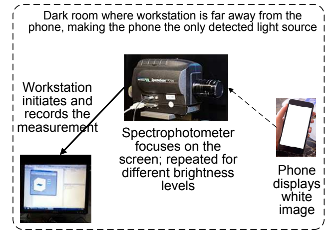



**Figure 4: Measurement of screen luminance.**

the trend of luminance threshold, we now seek the perceptual full brightness for smartphone VR.

According to Weber's Law, perceived change in luminance is proportional to the initial luminance and such a ratio is a constant [7]. In other words, the perceived change between the luminance triggering an eye response and the luminance producing the full-brightness sensation should be identical under normal lighting and VR HMD. Formally, we can express the relationship as,

$$\frac{Lum(B_{full}) - \Delta_{\min}(0)}{\Delta_{\min}(0)} = \frac{Lum(B_{full,prcpt}(t)) - \Delta_{\min}(t)}{\Delta_{\min}(t)} \quad (3)$$

where $B_{full}$ and $B_{full,prcpt}(t)$ is the full brightness (100%) in normal lighting and the perceptual full brightness in HMD. Note that $B_{full}$ is a constant value while $B_{full,prcpt}(t)$ is a time-varying value. Furthermore, $Lum()$ maps the brightness level ([0,100%]) in operating system to the luminance (cd/m$^2$), $\Delta_{\min}(t)$ is the luminance threshold ($\log_{10}$ cd/m$^2$) after spending time $t$ in a dark HMD, and $\Delta_{\min}(0)$ represents the luminance threshold just before one steps into the dark, i.e., in a normal lighting condition. Thus we have,

$$Lum(B_{full,prcpt}(t)) = \frac{Lum(B_{full})\Delta_{\min}(t)}{\Delta_{\min}(0)} \quad (4)$$

where $\Delta_{\min}(t)$ and $\Delta_{\min}(0)$ can be obtained from model (1).

To obtain perceptual full brightness $B_{full,prcpt}(t)$, it is necessary to know the relationship between luminance and brightness, i.e., $Lum(B)$. We obtain this relationship using real-world measurement. Figure 4 depicts the measurement setup. Similar as the luminance measurement in classic dark adaptation experiment [20], we display a white image on the smartphone screen as the single light source and configure the screen at multiple brightness levels. For each level, we use a Photo Research SpectraScan PR-715 spectrophotometer to measure the radiance, i.e., the light energy per unit solid angle per unit projected area, at different wavelengths. We then derive the luminance (cd/m$^2$) of a given brightness level by integrating the radiance at all wavelengths [24].

$$Lum = \int C * v(\lambda) * Rad(\lambda) d\lambda \quad (5)$$

where $C = 683$ is a constant converting watt to lumens, $v(\lambda)$ is the relative spectral sensitivity function representing different sensitivity of human vision on different wavelengths, and $Rad(\lambda)$ is the measured radiance at a wavelength $\lambda$.

Figure 5 exemplifies an observed power law model between the luminance and the brightness. This can be explained by the

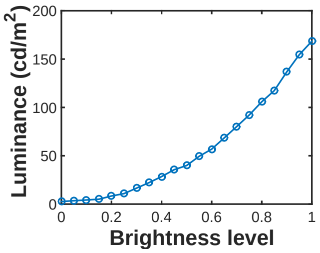



Figure 5: Luminance of various brightness levels for LG G Pro.

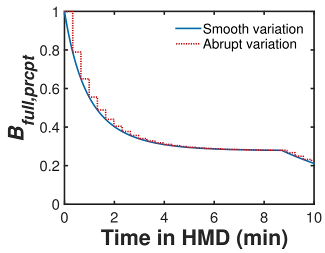



Figure 6: Variation of perceptual full brightness using different approaches.

gamma correction within the display hardware [9]. Using nonlinear regression, we obtain a model,

$$Lum(B) = a * B^b, 0 \leq B \leq 100\% \quad (6)$$

where $B$ is the brightness, and $a$ and $b$ are the training outputs dependent on smartphones. By replacing the value of $Lum(B_{full,prcpt}(t))$ into (6), we can dynamically derive the perceptual full brightness $B_{full,prcpt}(t)$ as $t$ changes.

## 3.3 Deciding Brightness Scaling Frequency

We have derived the time-varying perceptual full brightness in HMD. Since the derived $B_{full,prcpt}(t)$ is a continuous value, it is equally important to determine a scaling frequency when following the decaying trend. Figure 6 shows the scaling trend using different scaling frequency. Using a low scaling frequency can lead to abrupt and sudden brightness change, incurring flicker effect. On the other hand, although adopting an extremely high scaling frequency (greater than flicker fusion threshold [12]) can make the brightness transition smooth and nearly continuous, it is not always beneficial. The reason is that smartphones have a hardware limit on the maximum scaling frequency since the display panel suffers a nonnegligible response time after every OS request for brightness scaling. If we use a frequency higher than the hardware limit and send the display much more requests than it can handle, the display will need to buffer and process these requests one by one. This would slow down the decrease of brightness and reduce the energy saving.

We have confirmed this effect. We dynamically scale the brightness with a set of scaling intervals from 10 ms to 350 ms following the variation of perceptual full brightness. We invite 10 users to interact with a VR game (see Section 4 on user study setup) and ask them if they perceive any flicker effect or abrupt change in brightness. We also measure the display power during these 120-second VR sessions (see Section 4) for measurement setup). Figure 7 shows the display power and the percentage of users perceiving flicker (perceivability). As expected, a smaller scaling interval generates a finer grained sequence of brightness setting and thus more scaling requests. Under a given hardware limit, it takes more time to drop to a low brightness level and thereby consume more power. When the scaling interval is large enough, the display can exploit the full potential of dark-adaptation based brightness scaling and achieve a steady energy saving. However, if the scaling interval is too large, the brightness change and flicker can be perceived by

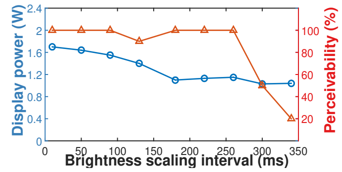



Figure 7: Scaling frequency impacts both power and experience.

Figure 8: Experimental setup for VR session energy measurement.

human eyes, degrading the user experience. Since both curves tend to be steady, we can safely choose the optimal scaling interval as 180 ms to balance the energy saving and user experience.

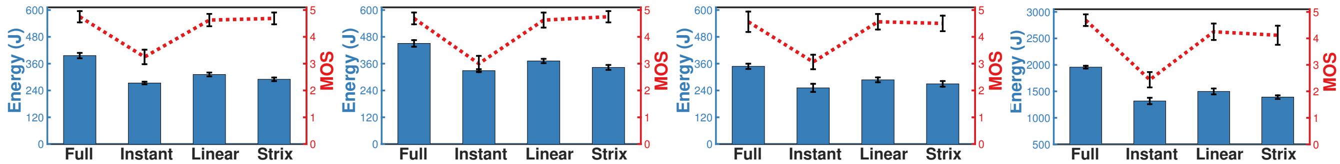
## 4 EVALUATIONS

**Experimental setup.** To evaluate Strix, we have implemented two most popular types of VR Apps. We first build a VR game, *Treasure Hunt*, by using `Google VR SDK/NDK`. We also implement a VR player to play a 360 degree video, *Balloon*, by extending Google ExoPlayer with `Rajawali` 3D engine. We achieve brightness scaling through Android's `WindowManager` API. A `Handler` is created for brightness control. We also synchronize brightness scaling with video and audio codec to support pause, rewind, etc.

Since there is no existing brightness scaling algorithms that explore VR vision, we compare Strix with the following benchmark systems: (a) *Full*: the default system with full brightness. (b) *Instant*: instantly setting a low brightness based on session duration and Figure 6 when a session starts, e.g., $B = 0.4$ for a 2-min session. This mimics the user behavior that directly selects a low brightness before the session. (c) *Linear*: linearly decreasing the brightness to the possible perceptual full brightness instead of using the trend in (1).

We first evaluate Strix by *Mean Opinion Score (MOS)*. We assess the subjective perception of Strix by a user study with 18 participants (age from 19 to 41, 12 males and 6 females, normal/corrected vision, 10 of them also in the study in Section 3.3). The participants are instructed to interact with the VR Apps freely in a large open space just as they would in a real-world home/office setting. We ask them to rate their satisfaction of brightness during the VR viewing. They are told that the highest score indicates comfortable/bright illumination and no brightness changes while lower scores imply more uncomfortable/darker illumination and more noticeable brightness changes. They are not informed about the possible brightness scaling strategies or the difference among the benchmark systems. To remove user memory bias, the four systems are shown to the users in a random order (but recorded by the administrator) under a given device/App/duration combination, as suggested in ITU single-stimulus protocol [19]. Before each test, we ensure that users have used normal viewing for 5 minutes and their eyes have adequately adapted from darkness to the normal lighting [4].

Another evaluation metric is *Session energy*. We measure total energy consumption of the device during a VR session. Considering that the user head-moving pattern cannot be repeated in multiple trials and that wiring a power meter to the smartphone within a




(a) Baseline case (b) VR 360 video (c) OLED device (d) 10-min session

**Figure 9: Strix achieves promising energy saving and satisfactory VR experience in various settings.**

HMD is difficult, we adopt the methodology in [13] for repeatable and easy measurement. The system first saves the head movement data automatically during the user study. In the energy measurement, we feed such user interaction trajectory to the VR rendering module and use it to replace the actual sensor reading. That way, the system can automatically switch the VR views without involving HMD or users. Figure 8 shows the energy measurement setup using Monsoon power meter.

**Baseline case.** We first perform the system-level evaluation on a LG G Pro phone and a Homido V2 VR headset for a 120-second VR game session. Figure 9a shows that Strix substantially reduces system energy while achieving comparable VR experience to the default Full system using fixed brightness. On average, Strix consume 27% less system energy, or 52% less display energy, than Full. This implies that dark adaptation indeed exists in HMD. Furthermore, by applying a proper scaling frequency, we can remove the potential flicker effect in brightness scaling. In contrast, although Linear can also save energy thanks to the same dark adaptation based scaling, it consumes 8% more system energy, or 22% more display energy than Strix. The reason is that Linear does not consider the delicate and exact trend of dark adaptation. Assuming in Figure 6, if we plot a linear brightness-decreasing curve from 1.0 at the beginning down to 0.2 at 10th minute, there would be a significant gap between the scaled brightness for Linear and Strix. This makes it fail to exploit the full potential of dark adaptation, leading to a degraded energy efficiency. It is important to note that the theoretical energy saving of Strix over Linear by using two brightness decreasing curves is noticeably more than the measurement results. We suspect this is due to the insufficient number of measurement trials, which fails to average the energy measurements. Moreover, directly applying a lower brightness using Instant results in a slightly lower energy. Nevertheless, the user experience is far from desirable since the user has to view a very dark ($B = 0.4$ in this case) content at the beginning of session without adequate eye adaptation.

**Impacts of App types.** We then evaluate Strix in a VR 360 video session. Figure 9b shows that Strix again saves a large amount of energy, i.e., 23% less system energy than Full and 51% less display energy, without sacrificing the user experience. As VR video is a networked system where the content are delivered to the smartphone player from a remote server, it incurs additional video transport and decoding energy, which increases the total system energy. Therefore, even though we observe a similar amount of display energy saving on VR video, its percentage of energy saving on the device is slightly degraded compared to VR game.

**Impacts of display type.** Instead of the LCD phone in the baseline case, we further use a Samsung Note 4 with OLED display to evaluate the VR game. Figure 9c demonstrates that all the benchmark systems achieve a lower energy compared to Figure 9a. This is due to the different energy efficiency in two types of display. Brightness scaling on OLED is equivalent to displaying dark content. Since OLED is generally more power efficient when displaying dark pixels, Note 4 consume less energy even though it has a larger screen size. Moreover, despite the lower energy consumption, we can still observe a 22% energy reduction. This result indicates the wide applicability of Strix on various smartphones.

**Impacts of session duration.** We repeat the baseline case with an extended duration (600 seconds). Instant will now apply the 20% brightness when the session starts while Linear will decrease the brightness to 20% linearly. Figure 9d shows that although all systems consume much more energy due to the extended session, the energy savings of Strix remain unchanged. We also observe a MOS drop for the 600-sec session. In Instant, the VR content would be shown at 20% brightness at the beginning, which is unacceptable for almost every user. Therefore, the average MOS is only 2.4. Since the brightness in Linear and Strix decreases gradually, the negative impact of 20% brightness is less obvious. However, if a longer session is initiated and the brightness decreases based on Figure 6 without any restriction, the MOS may degrade continuously. We discuss a solution in Section 5.

## 5 DISCUSSION AND FUTURE WORK

**Brightness lower bound.** To address the negative effects caused by continuously decreasing brightness in a long VR session, we can introduce a brightness lower bound below which the brightness will never drop. This can serve as a user knob to balance energy saving and user experience.

**Model improvement.** A future direction is to use crowd sensing to collect a more diverse dataset to improve the general dark adaptation model. For example, users with different age and gender may present distinct dark adaptation curves. We may have the chance to further save energy for some insensitive users. The intensity and duration of pre-adapting light (e.g., outdoor or indoor) also matters. We can use light sensor to detect the pre-HMD status and optimize the adaptation. A deep study of how much impact these factors would bring on the dark adaptation model and which of these factors play a dominant role on dark adaptation is needed to further calibrate the current model.

**Eye fatigue.** While the users do not express feeling of tiredness or strain during our preliminary 2-minute user study, the long-term effect of vision health when using Strix needs further investigation. It is critical to guarantee that under regular VR viewing duration the brightness scaling would not introduce abnormal eye fatigue and impact vision health.

**Content illumination.** Strix focuses on ambient illumination for brightness scaling, which is identical to default smartphone auto brightness using light sensor. A full-scale study is needed to understand whether or not the content illumination on the screen will impact the dark adaptation and how much the impact is. Similarly, in addition to the brightness scaling done in Strix, we can also compensate the pixel luminance and then scale the brightness one more time. This approach considers content illumination and hence can introduce extra energy-saving space. In addition, since we have full control for individual pixel on OLED, it is expected that we can manipulate regions of content to save energy while preserving/enhancing the content contrast.

**Overhead.** The computation of brightness change is minimal by using (4) and (6). Strix can be implemented on smartphones with negligible overhead. However, if advanced pixel-level processing is used to further reduce energy, it opens a challenge of striking a tradeoff between display energy saving and energy overhead.

## 6 RELATED WORK

Display energy reduction for LCD [17, 27] aimed to dim LCD backlight. In contrast, pixel-level control for OLED were proposed based on usability [9, 23] and fidelity [6]. A joint display and transport energy optimization was presented in [26]. These schemes are complementary to Strix since Strix drops the perceptual full brightness. Combining them with Strix is expected to achieve more energy savings.

To improve smartphone VR, FlashBack [3] rendered and cached VR images locally to provide low-latency and high-framerate experience. Furion [15] separated the rendering of background and foreground onto cloud and smartphone, respectively, to enable high-quality smartphone VR. Qian et al. [21] predicted the head movement in VR video and only downloaded some viewports to save the network bandwidth. Abari et al. [1] used mmWave to deliver huge VR data in order to remove the wire in desktop-based VR. FocusVR [28] rendered a smaller VR view to improve OLED efficiency in smartphone VR. In this paper, we steer to a new direction in exploring the physiological effects of dark adaptation to optimize general display efficiency.

## 7 CONCLUSION

In this paper, we take a important step in exploiting HMD vision to optimize smartphone VR. We present Strix, a brightness scaling system to utilize the full potential of dark adaptation and ensure the smooth brightness perception. Real-world evaluations show that Strix achieves substantial (25% on average) energy reduction without degrading user viewing. We believe the success of Strix can enable a suite of future works studying other HMD vision effects, e.g., binocular vision rivalry, to optimize smartphone VR.

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## REFERENCES


[1] O. Abari, D. Bharadia, A. Duffield, and D. Katabi. 2016. Cutting the Cord in Virtual Reality. In *ACM Workshop on Hot Topics in Networks (HotNets)*.

[2] L. Allen and K. Dallenbach. 1938. The effect of light-flashes during the course of dark adaptation. *The American Journal of Physiology* 51 (July 1938), 540–548.

[3] K. Boos, D. Chu, and E. Cuervo. 2016. FlashBack: Immersive Virtual Reality on Mobile Devices via Rendering Memoization. In *MobiSys*.

[4] Encyclopedia Britannica. 1987. Sensory Reception: Human Vision: Structure and Function of the Human Eye. 27 (1987).

[5] A. Carroll and G. Heiser. 2010. An analysis of power consumption in a smartphone. In *USENIX annual technical conference (USENIXATC)*.

[6] X. Chen, Y. Chen, and C. J. Xue. 2015. DaTuM: dynamic tone mapping technique for OLED display power saving based on video classification. In *ACM/EDAC/IEEE Design Automation Conference (DAC)*.

[7] Tom N Cornsweet and HM Pinsker. 1965. Luminance discrimination of brief flashes under various conditions of adaptation. *The Journal of Physiology* 176 (March 1965), 294–310.

[8] International Data Corporation. https://goo.gl/GhMTqA. Worldwide Quarterly Augmented and Virtual Reality Headset Tracker.

[9] M. Dong and L. Zhong. 2011. Chameleon: a color-adaptive web browser for mobile OLED displays. In *MobiSys*.

[10] Mian Dong and Lin Zhong. 2012. Chameleon: A Color-Adaptive Web Browser for Mobile OLED Displays. *IEEE Trans. Mobile Comput.* 11 (May 2012), 724–738.

[11] M. Dong and L. Zhong. 2012. Power Modeling and Optimization for OLED Displays. *IEEE Trans. Mobile Comput.* 11 (Sept. 2012), 1587–1599.

[12] A. Iranli, Wonbok Lee, and M. Pedram. 2006. HVS-Aware Dynamic Backlight Scaling in TFT-LCDs. *IEEE Trans. VLSI Syst.* 14 (Oct. 2006), 1103–1116.

[13] N. Jiang, V. Swaminathan, and S. Wei. 2017. Power Evaluation of 360 VR Video Streaming on Head Mounted Display Devices. In *NOSSDAV*.

[14] GA Koulieris, B. Bui, M. Banks, and G. Drettakis. 2017. Accommodation and Comfort in Head-Mounted Displays. *ACM Transactions on Graphics* 36 (July 2017), 11.

[15] Z. Lai, Y. C. Hu, Y. Cui, L. Sun, and N. Dai. 2017. Furion: Engineering High-Quality Immersive Virtual Reality on Today's Mobile Devices. In *MobiCom*.

[16] K. Lee, D. Chu, E. Cuervo, J. Kopf, Y. Degtyarev, S. Grizan, A. Wolman, and J. Flinn. 2015. Outatime: Using speculation to enable low-latency continuous interaction for mobile cloud gaming. In *MobiSys*.

[17] C.-H. Lin, P.-C. Hsiu, and C.-K. Hsieh. 2014. Dynamic Backlight Scaling Optimization: A Cloud-Based Energy-Saving Service for Mobile Streaming Applications. *IEEE Trans. Comput.* 63 (Feb. 2014), 335–348.

[18] R. Messing and F. Durgin. 2005. Distance perception and the visual horizon in head-mounted displays. *ACM Transactions on Applied Perception* 2 (July 2005), 234–250.

[19] ITU methodology for the subjective assessment of the quality of television pictures. 2012. ITU-R BT.500-13. (2012).

[20] E. N. Pugh. 1975. Rushton's paradox: rod dark adaptation after flash photolysis. *The Journal of Physiology* 248 (June 1975), 413–431.

[21] F. Qian, L. Ji, B. Han, and V. Gopalakrishnan. 2016. Optimizing 360 video delivery over cellular networks. In *ACM Workshop on All Things Cellular: Operations, Applications and Challenges*.

[22] D. Shin, Y. Kim, N. Chang, and M. Pedram. 2013. Dynamic driver supply voltage scaling for organic light emitting diode displays. *IEEE Trans. Comput.-Aided Design Integr. Circuits Syst.* 32 (July 2013), 1017–1030.

[23] K. W. Tan, T. Okoshi, A. Misra, and R. K. Balan. 2013. FOCUS: a usable & effective approach to OLED display power management. In *UniComp*.

[24] Thorlabs. Radiometric vs. Photometric Units. (https://www.thorlabs.de/catalogPages/506.pdf).

[25] M. Winterbottom, R. Patterson, B. Pierce, J. Gaska, and S. Hadley. 2015. Visibility of monocular symbology in transparent head-mounted display applications. In *Proc. of SPIE 9470*.

[26] Z. Yan and C. W. Chen. 2016. RnB: rate and brightness adaptation for rate-distortion-energy tradeoff in HTTP adaptive streaming over mobile devices. In *MobiCom*.

[27] Z. Yan, Q. Liu, T. Zhang, and C. W. Chen. 2015. Exploring QoE for Power Efficiency: A Field Study on Mobile Videos with LCD Displays. In *ACM International Conference on Multimedia (MM)*.

[28] T Kiat Wee, E Cuervo, RK Balan 2016. FocusVR: Effective & Usable VR Display Power Management. In *MobiSys Companion*.