

Peripheral Light Cues as a Naturalistic Measure of Focus

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ABSTRACT

Deeply immersive experiences are intrinsically rewarding; evoking them for another is a cornerstone of success in artistic or design practice. At the same time, modern interfaces have created a state of 'partial continuous attention', and frequent self-interruption is more common than ever. In this paper, we propose a smart-glasses based interaction to quantify self-interruption dynamics in naturalistic settings, in which a slowly changing peripheral LED is monitored as a secondary task by the user. We demonstrate that this interaction captures useful information about a user's state of engagement in real-world conditions. These data can provide designers and artists novel, objective insight into the depth of immersive experience evoked in real-world settings.

CCS CONCEPTS

- **Human-centered computing** → **Ubiquitous and mobile computing design and evaluation methods; User centered design;**
- **Hardware** → **Sensor devices and platforms.**

KEYWORDS

flow, attention, wearable, ecological validity, ambulatory measurement, phenomenology, psychometric, focus, absorption

ACM Reference Format:

David B. Ramsay and Joseph A. Paradiso. 2022. Peripheral Light Cues as a Naturalistic Measure of Focus. In *ACM International Conference on Interactive Media Experiences (IMX '22)*, June 22–24, 2022, Aveiro, JB, Portugal. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3505284.3532984>

1 INTRODUCTION

Deep attention is an integral part of meaningful experiences and 'flow' states; experiences are best when users are focused, immersed, and absorbed. [13, 18, 22, 26] Evoking this quality of attention is difficult in modern life, however. Modern technology incentives frequent task switching and interruption; attention spans have shortened enough that some scholars suggest that we live in a state of 'continuous partial attention'. [7] These frequent interruptions have trained us to self-interrupt even absent exogenous cues [4]; over half of typical interruptions are self-generated. [11] These shifts in our attention come with huge social and personal costs; [15] they also raise the difficulty for designing experiences that capture and hold user attention.

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IMX '22, June 22–24, 2022, Aveiro, JB, Portugal
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ACM ISBN 978-1-4503-9212-9/22/06.
<https://doi.org/10.1145/3505284.3532984>

One major objective for HCI practitioners, designers, and artists is to create deep states of attention that indicate psychological immersion; however, our ability to measure the quality of a user's attention is poor. State-of-the-art techniques typically capture either self-report or examine overt attention (i.e. eye-gaze) [8, 12, 20, 27]. In this paper, we present a novel interaction to measure attention dynamics in naturalistic settings. Our contributions are as follows:

We design and create a novel, wearable, and discrete interaction to measure self-interruption dynamics in daily life. This interaction is built on top of the Captivates Smartglasses platform from [3]; the glasses present a slow color change in the periphery of the user's visual field, gradual enough that users' attention will not be drawn to it. When the user notices a shift in color because they have scanned their environment, they indicate that with a companion application. We run two small pilot studies to test the efficacy of this interaction and demonstrate success in creating an interaction that is 'change-blind' to study participants and captures data related to their state of engagement. We discuss and analyze these preliminary results.

We discuss future applications and design considerations of this interaction for studying naturalistic attention dynamics and for quantifying the immersive success of designed experiences.

2 BACKGROUND

We live in a world with constant notification and interruption that fractures our attention. Workplace interruptions occur every 4-11 minutes; 70% of the roughly 90 emails we receive in a day are opened within 6 seconds. [16] External interruptions make us more likely to self-interrupt in the hour after they occur [4].

Fortunately, notifications can be designed to be more or less distracting from our primary task. [14] Researchers have prototyped notifications to allow deep focus to proceed uninterrupted by designing them right at the threshold for capturing attention. The user's attentional state is the primary factor that determines whether they notice an aural cue (by modifying background music) [1] or a visual one. [9]

At the other end of the design spectrum, some cues are impossible to ignore. Motion and luminance changes powerfully capture attention. [21] When motion cues are masked— including using gradual fades— large visual changes are difficult to spot, regardless of the magnitude of change in contrast or color. [23] This phenomena is known as 'change-blindness'. Moreover, research on 'inattention blindness' supports the idea that we are blind to large, obvious visual changes in the center of our visual field when focused on a task. [10]

Some distractors are more perceptually salient than others. However, even given a task, we have no accepted standard for measure

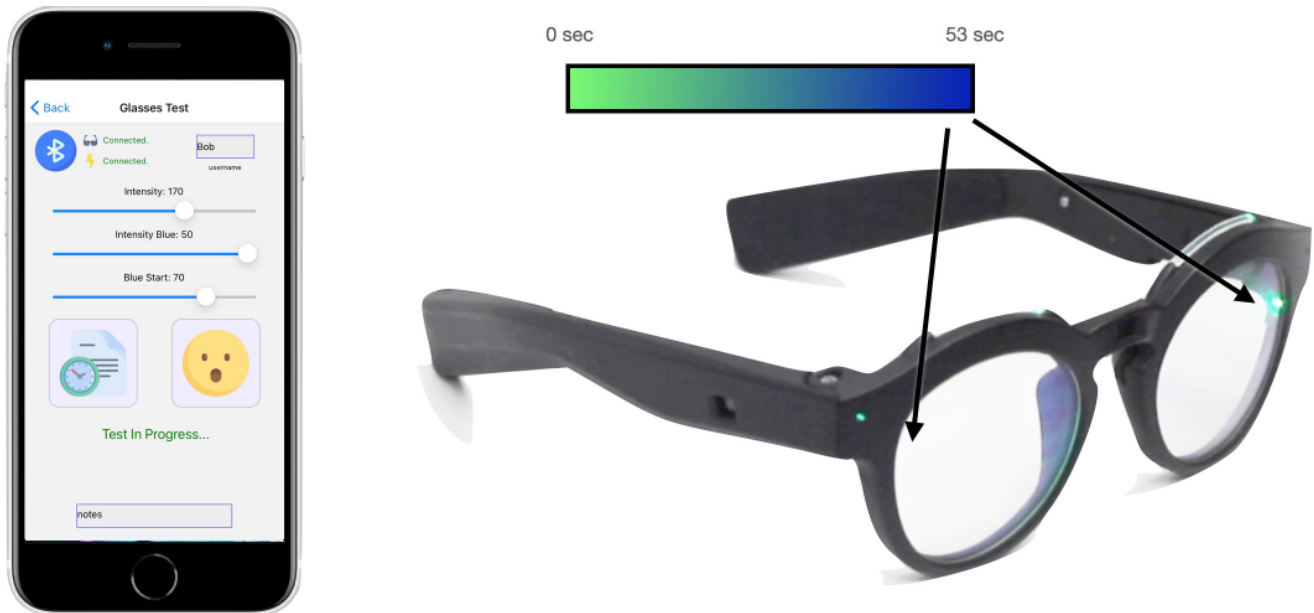


Figure 1: The Captivates Smartglasses platform presented in [3] is used to measure self-interruption behavior. Two symmetrical peripheral LEDs slowly change from green to blue over 53 seconds; when the user notices the change, they indicate it by hitting the 'surprised' emoji in the companion application which is left open on the table near them). These transitions are spaced 10-20 minutes apart to give the user sufficient time to achieve a state of deep focus on their primary task. The change is slow and gradual to minimize the probability of drawing attention to itself.

our sensitivity to chromatic or luminous changes under varied ambient lighting conditions; the best models estimate cone absorption in the retina. [2, 28] Ambient light levels mediate visual detection through pupil dilation; a smaller aperture gives better spatial resolution while a larger one gives higher signal to noise and more light. [5, 19] Large pupils may thus give an advantage to detection of faint peripheral stimuli. [17] A simple relationship between low-level perceptual changes in brightness or contrast and attentional capture is impossible, though; for example, luminance changes characteristic of a new object in a scene will capture attention more readily than twice the difference at a less-surprising location. [24]

Many factors influence our perception of task-irrelevant, peripheral distractors. Motion and luminance differences– especially unexpected ones close to our visual focus– are most likely to grab our attention. While ambient conditions likely effect our ability to discriminate peripheral stimuli, this is a second-order effect relative to our psychological factors like expectation and attentional state.

2.1 Measurement Techniques

Mainstream measures of engagement rely on self-assessments [6] that are biased by demand characteristics and peak-end memory distortions and fail to capture uncertainty well. One more quantitative approach to cognitive state inference is the peripheral detection task (PDT), an ISO-standard test to measure cognitive load while driving. [29] This test has been updated to use a head-mounted peripheral light as a secondary stimuli while driving (hDRT, or head-mounted detection response task) [25].

In the hDRT, a red LED is turned on rapidly (every 3-5 sec), at constant intensity, long duration (1 sec), and reliable noticeability (>95 in practice– reaction times are the primary hDRT measure). When the participant notices this light, they hit a button; response latency is the primary measure of task load.

DRTs do not disambiguate between noticing and reacting (there is evidence of physical response conflict); also, due to the consistent nature of the task, participants treat it as a secondary goal for which they strategically allocate attention [29]. While useful to characterize multi-tasking load under intense driving conditions, this rapid and consistent dual task paradigm is a poor fit for the naturalistic study of deep focus.

3 CAPTIVATES

We design a new interaction using the Captivates smart glasses platform presented in [3]. The form factor gives us access to two symmetrical RGB LEDs mounted in the outside peripheral vision of the user, controlled by LED driver ICs that enable ratiometric and logarithmic PWM dimming. Figure 1 details the intervention design– when the user notices a subtle, gradual change in color of the LED (which occurs every 10-15 minutes) they hit a button to indicate it. Their delay is an indicator of the frequency of their self-interruption. The specific design decisions were based on an iterative design process to isolate a subtle, gradual, but distinct peripheral change. The glasses include 300 mAh battery capacity that allows the intervention to run continuously for over 7 hours



Participant #	1	2	3	4	5	Overall
Low Warm Light (<i>avg (std)</i>)	4.6 (1.4)	5.2 (1.5)	2.5 (1.1)	9.0 (1.2)	5.9 (1.5)	5.4 (2.5)
Bright White Light (<i>avg (std)</i>)	4.6 (1.5)	6.3 (2.4)	5.5 (1.4)	8.1 (0.6)	6.1 (1.1)	6.2 (1.9)

Figure 2: To test the effect of variable lighting conditions on perceptual acuity of the LED color shift, we used a specially designed lighting room set to two extremes; a bright white light high blue light spectrum- Figure Left) and a low warm light (Figure Right). Participants were asked to look at an 'X' on the wall and pay attention to the LED color change in their periphery, indicating when they noticed the transition in the application. Participants were exposed to ten transitions in each lighting condition; the order of exposure to each condition was counterbalanced across participants. Results from these calibration sessions are shown in the table.

per charge; it is also a socially acceptable form factor that enables daily use in normal life without inducing self-conscious behavior.

3.1 Calibration Test

For our initial test, we measure (1) when during the transition from green-to-blue an attentive user notices the change, and (2) how much variability various lighting conditions introduce. Five users sat in a closed rectangular room outfitted with a full Color Kinetics lighting system (programmable with color temperatures between 2300K and 7000K). While looking at an 'X' on the wall in front of them, they indicated when they noticed the light in their peripheral vision shift colors. To maintain attention, the transition was sped up 3x from the typical intervention to 17 seconds. They repeated this task twenty times with random delay— ten under bright white lighting conditions and ten under low warm lighting conditions (counter-balanced). Low warm lighting is most favorable to the task: dilated pupils give the best peripheral detection and the most contrast with the background (warm light has very little of the target blue wavelength). In contrast, the bright white light has much less contrast in the blue spectrum and constricts the pupils.

Results are shown in Figure 3; there was not a significant difference in the participants ability to notice the color shift across light conditions. Across all 100 trials, the best and worst cases for perceiving the change were between 12 and 65 through the transition.

3.2 Primary Test

In our main test, seven users experienced the intervention in Figure 1 as they went about their daily lives, with an open iPad within reach to indicate their awareness of the LED changing. We collected over 19 hours of data, with transitions spaced 10-15 minutes after any indication to allow the user to regain task focus. The data is represented in Figure 2. The longest a participant went without noticing the light change was 15 minutes; 35 of the transitions were noticed after the transition had fully completed, with the vast majority significantly delayed (74 of those were >30 seconds after the light change had completed). Four of the seven users had delays of 5 minutes or more in noticing at least once, indicating a deep state of focus on their primary task.

4 DISCUSSION AND FUTURE WORK

Whether or not a participant notices a gradual, peripheral color change is dependent on environmental lighting and attentional state. We designed an intervention with the hope that users would be change-blind to it. Our initial results imply minimal variability in noticing for vigilant user across extreme ambient lighting conditions; this variability is small compared with the the delays we find as users engage in their day. Our results support our hypothesis that this intervention quantitatively captures useful insight into self-interruption and environmental awareness in real world settings.

In our future work, we will collect more data, and build probabilistic models to make strong inferences about an individual's attention based on it. Future experiments may introduce longer

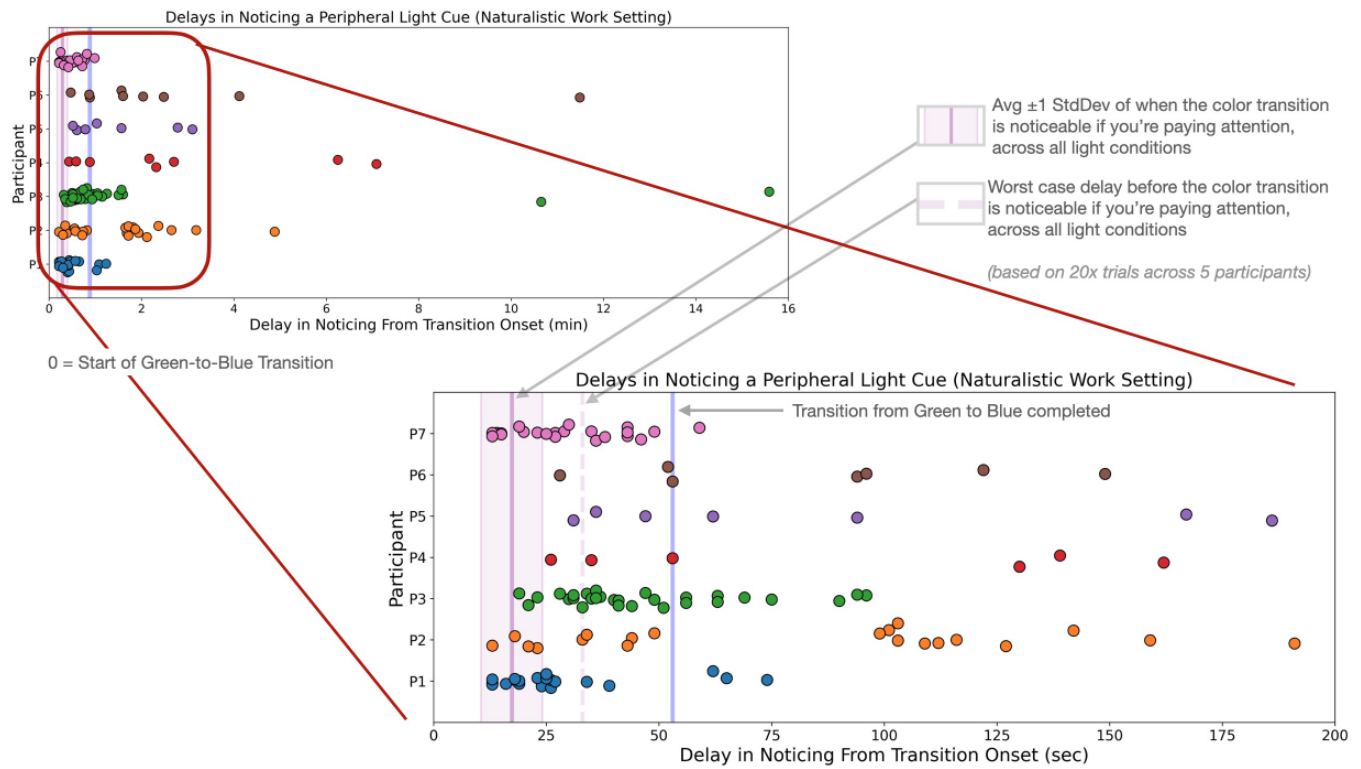


Figure 3: Initial results from seven participants wearing the interface in natural work/social settings for a minimum of 2 hours each (19.3 hours captured total). Data points represent the delay from a transition starting to when the user noticed it. Included in the plot are indicators of when the transition becomes observable based on the calibration data (purple), as well a worst case indicator over the 100 calibration trials (dotted)– this represents the worst case moment, across lighting conditions, that we’d expect the transition to become obvious if the user was paying attention.) The slow transition completes at 53 seconds (blue). We see several data points in which users didn’t notice the transition for many minutes after it was completed (top left); a zoomed view of the first few minutes after transition onset are shown in the bottom right. As expected, noticing delay follows a roughly log-normal distribution for each user.

delays between transitions to allow users more time to achieve a deep state of focus; this trade-off between quantity and quality of data is unstudied. Though it appears the effects of ambient lighting are minor (and can be modeled as noise), we also haven’t tested for interaction effects between attentional state and ambient lighting. Future work may extend our understanding of ambient lighting conditions using tightly controlling lighting or by measuring ambient light levels with an additional wearable.

5 CONCLUSIONS

In this paper, we presented a novel interaction design to study self-interruption and immersion across naturalistic contexts. Users indicate when they have noticed a gradual, subtle, peripheral light cue change– a transition that only happens every 10-15 minutes. In two small pilot studies we have demonstrated that ambient lighting levels minimally affect perception of this transition, and a significant portion of these changes are unnoticed for several minutes by our users in naturalistic settings; attentional state is thus the primary causal precursor of this data, with a large impact on the measured delays.

We believe this interaction can improve our understanding of the dynamics of human attention, and provide quantitative insight into design’s impact on the creation of immersive, engaging, meaningful experience. This approach represents a quantitative move forward toward personalized, adaptive, and empirically grounded immersive design.

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