iLid: Eyewear Solution for Low-power Fatigue and Drowsiness Monitoring

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ABSTRACT

The ability to monitor eye closures and blink patterns has long been known to enable accurate assessment of fatigue and drowsiness in individuals. Many measures of the eye are known to be correlated with fatigue including coarse-grained measures like the rate of blinks as well as fine-grained measures like the duration of blinks and the extent of eye closures. Despite a plethora of research validating these measures, we lack wearable devices that can continually and reliably monitor them in the natural environment. In this work, we present a low-power system, iLid, that can continually sense fine-grained measures such as blink duration and Percentage of Eye Closures (PERCLOS) at high frame rates of 100fps. We present a complete solution including design of the sensing, signal processing, and machine learning pipeline and implementation on a prototype computational eyeglass platform.

CCS CONCEPTS

• **Human-centered computing** → **Mobile devices**; User studies; • **Computing methodologies** → *Interest point and salient region detections*; • **Applied computing** → *Consumer health*.

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1 INTRODUCTION

There is significant need for a device that can continuously monitor fatigue, since this has implications for a wide range of application domains ranging from personal safety to health monitoring. One modality that has long been known to provide a good measure of fatigue is eye monitoring. Many decades of experimental studies involving eye monitoring have identified that PERCLOS (the percentage of time in which the eye is more than 80% closed), blink duration, and blink frequency are the most significant features of interest for predicting the level of fatigue [Ingre et al. 2006; Schleicher et al. 2008; Stern et al. 1994; Wierwille et al. 1994].

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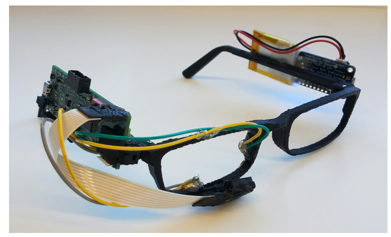

Figure 1: Eyeglass platform containing an eye-facing imager, two NIR LEDs, and a PCB board with the micro-controller, Bluetooth, and other modules on the left, as well as the battery board on the right [Mayberry et al. 2014, 2015].

Despite our understanding of how to measure fatigue, we lack good instruments to measure these eye parameters robustly in natural settings. In constrained environments such as vehicles, the environment can be instrumented with cameras to allow remote monitoring. Alternately, commercial eye trackers intended for short-term episodic use can provide such measures and have been available for more than a decade (e.g., SMI [smi 2007] and Tobii [tob 2015]). But transitioning from technology that works in episodic and controlled settings to natural environments has been challenging. There is a need for a truly wearable device that is low-power, portable, and provides accurate measures of eyelid movement, while being robust to confounders present in everyday scenarios.

In this paper, we design a system, iLid, that is able to extract key features of fatigue at low power and high frame rate from a wearable eye tracker. We develop methods that can dramatically reduce the cost of sensing and processing by sampling a small subset of pixels on an imager (a few columns of pixels) and processing these pixels in real time to extract the salient features for fatigue detection. We develop lightweight classification-based methods to extract blink and eyelid features such as blink duration, blink rate, and eyelid closure patterns.

2 iLid SYSTEM DESIGN

In this section, we provide a brief overview of the working of iLid (for details please refer to the full paper [Rostaminia et al. 2017]).

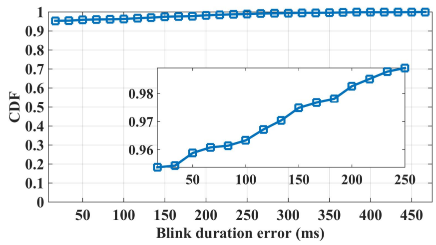

Figure 2: Blink duration measurement error CDF.

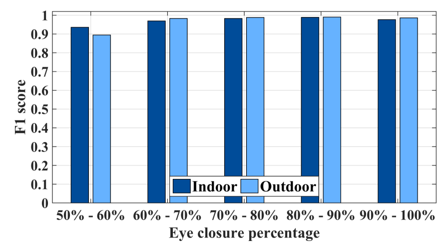

Figure 3: Eyelid detector performance in different eye closure states.

2.1 Upper Eyelid Detection

The first stage in our computational pipeline is upper eyelid detection. Reducing the amount of data sampled at the imager is crucial to minimizing power consumption and increasing frame rate. Our eyelid detection pipeline limits the sampling to only a block of 4 columns in the middle of the image, in which the upper eyelid is roughly in its highest position. Such column sampling makes intuitive sense since we are focused on the eyelid; the use of a few columns rather than a single column also helps to reduce noise that may be observed due to intrinsic noise in a low-power imager, specular reflection of the NIR LED on the image, and other such considerations.

2.2 Blink Detection

Once the upper eyelid is detected, the next stage is to determine blinks. Blinks can be placed into a few categories based on their duration and pattern and that makes template matching an ideal method for blink detection. The template matching process is a simple normalized cross-correlation computation. We normalize the eyelid position time-series to remove differences in the height of the blink across individuals. Then we sweep the eyelid data with each of the templates (three templates for fast, normal, and slow blinks) and calculate the dot product of each subsection with the corresponding template to obtain a similarity score. Given the scores, we then map the continuous output (matching scores with the three templates) to a categorical output (blink vs. not-blink) with a linear logistic regression classifier [Friedman et al. 2001].

2.3 Drowsiness Estimation

Once blinks are detected and their durations are measured, the corresponding frames are removed from the upper eyelid position time series in order to measure PERCLOS. For PERCLOS estimation, we calculate the number of frames in which the eye is more than 80% closed *excluding the blinks* [Tijernia et al. 1999] compared to when the eye is fully open.

3 PERFORMANCE

We present a brief evaluation of iLid on data collected from 16 users, 10 male and 6 female. The experiment consists of the participants watching a short animated movie for 5 minutes while wearing the computational glasses (shown in Figure 1) in both indoor and outdoor (with uncontrolled and varying illumination conditions) environments. We used this data to perform experiments testing iLid's effectiveness.

3.1 Blink Detection

We first evaluate the performance of the blink detection algorithm in terms of its ability to recognize blink instances. This is evaluated using precision, recall and F1 score. We use leave-one-out cross validation. Our dataset from 16 subjects included 643 blink instances in the indoor dataset and 1117 blink instances in the outdoor dataset.

Table 1 shows that we achieve high precision (roughly 0.95) and high recall (roughly 0.85) for both indoor and outdoor datasets, which validates its ability to operate effectively across different illumination conditions that one might encounter in a real-world setting.

Table 1: Blink detection accuracy (over 1760 blink instances).

Dataset	Precision	Recall	F1 score
indoor	0.96	0.85	0.90
outdoor	0.95	0.84	0.89

3.2 Blink duration estimation

Figure 2 shows the error CDF of measured duration of correctly detected blinks. Our methods perform extremely well in this regard — more than 95% of the detected blinks had error of less than 17ms (i.e. less than 10% of a typical 200ms blink).

3.3 PERCLOS estimation

In this evaluation, we look at how well we determine PERCLOS. Since PERCLOS is essentially a measure of the percentage of eye closure, we divide frames into different stages of eye closure, and see how well we can detect these stages. Figure 3 depicts eyelid detector's performance in five different eye closure states corresponding to the eye being 50-60%, 60-70%, 70-80%, 80-90%, and 90-100% closed. As can be seen in the figure, the detector shows excellent performance across all the eye closure states. Of particular interest to PERCLOS estimation is the accuracy for detecting when the eye is more than 80% closed. The accuracy of this detection is 97.5%, which shows that our methods are effective for determining PERCLOS.

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